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Novel DTN Mobility-Driven Routing in Autonomous Drone Logistics Networks

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Abstract

Drones have become prevalent for the delivery of goods by many retail companies such as Amazon and Dominos. Amazon has an issued patent that describes how drones scan and collect data on their fly-overs while dropping off packages. In this context, we propose a path optimization algorithm for a drone multi-hop communications network that can carry and forward data in addition to its primary function of parcel deliveries. We argue that traditional Delay Tolerant Networking (DTN) based protocols may not be efficient for this purpose. Therefore, this paper proposes a new DTN-based algorithm that optimizes drone flight paths in conjunction with optimized routing to deliver both parcels and data in a power efficient way and within the shortest possible time. We propose a heuristic algorithm called Weighted Flight Path Planning (WFPP) that priorities the data packets in an exchange pool in order to create an optimized path for the drones. Our approach is to determine a weight for each packet based on the packet's remaining time to live, priority, size, and location of the packet's destination. When two drones meet each other, they exchange the high weighted packets. Simulation studies show that WFPP delivers up to 25% more packets compared with EBR, EPIDEMIC, and a similar path planning method. Also, WFPP reduces the data delivery delays by up to 66% while the overhead ratio is low.

Keywords

autonomous, drone, logistics, routing, networks, dtn, novel, mobility-driven

Disciplines

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Novel DTN Mobility-Driven Routing in Autonomous Drone Logistics Networks

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ABSTRACT Drones have become prevalent for the delivery of goods by many retail companies such as Amazon and Dominos. Amazon has an issued patent that describes how drones scan and collect data on their fly-overs while dropping off packages. In this context, we propose a path optimization algorithm for a drone multi-hop communications network that can carry and forward data in addition to its primary function of parcel deliveries. We argue that traditional Delay Tolerant Networking (DTN) based protocols may not be efficient for this purpose. Therefore, this paper proposes a new DTN-based algorithm that optimizes drone flight paths in conjunction with optimized routing to deliver both parcels and data in a power efficient way and within the shortest possible time. We propose a heuristic algorithm called Weighted Flight Path Planning (WFPP) that priorities the data packets in an exchange pool in order to create an optimized path for the drones. Our approach is to determine a weight for each packet based on the packet's remaining time to live, priority, size, and location of the packet's destination. When two drones meet each other, they exchange the high weighted packets. Simulation studies show that WFPP delivers up to 25% more packets compared with EBR, EPIDEMIC, and a similar path planning method. Also, WFPP reduces the data delivery delays by up to 66% while the overhead ratio is low.

INDEX TERMS Delay tolerant network, drones, intelligent transportation systems, forwarding strategy, dynamic mobility models, EBR, EPIDEMIC, smart cities, routing, optimization algorithms, unmanned aerial vehicles, vehicular networks.

I. INTRODUCTION

Drones or Unmanned Aerial Vehicles (UAV) are aircraft that can either operate autonomously or be flown under remote control [1]–[3]. Drones were initially used in military and civilian applications [4], [5], such as surveillance, policing, firefighting, and search and rescue missions [6]. More recently, retail companies such as Domino's, UPS and Amazon are investing to develop drones in order to make fast deliveries to their customers [7]. Theoretically, this should improve the customers' experience as they receive purchased items within minutes after purchase. Also, in terms of cost, at least in theory again, drones can significantly reduce the delivery cost compared with other traditional logistics networks. As an example, Amazon claims that the estimated

cost per mile for a delivery drone is five cents whereas a motor vehicle with the fuel consumption of 10L/100km costs approximately 17 cents per mile in addition to other costs such as vehicle depreciation and maintenance [7].

Given there is such a growing interest in drones, it is only natural for value added services to be introduced in addition to parcel services. For example, Amazon has a patented technology that enables a delivery drone to scan and collect data from houses on its flight path while dropping off parcels [8]. It is not hard to imagine that more in-depth data can be collected. For instance, drones can collect information about vehicles, the exterior of homes and any property visible from the outside and use that for marketing related products. Granted, that most people may not feel comfortable with such data collection, but in reality, much more data is already being harvested through such applications as Google Earth and Facebook. Furthermore, Amazon has been active in making

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drones more useful as a delivery vehicle and has patented hand gesture technology that allows a customer to get the drone's "attention" [9], i.e., a passing drone can be called to your location by simply waving a hand and calling it down.

Data communication in such a drone network is challenging as there might be no contemporaneous (end-to-end) connections established through intermediate nodes from source to destination. This is due in part to the mobility of drones that create a highly dynamic network topology. Moreover, the network may have limitations such as short radio ranges or low node density. Such disjoint networks are referred to as Delay Tolerant Networks (DTN). Traditional Transport and routing protocols such as TCP/IP do not work, as a path needs to exist between source and destination for the duration of the connection. In this context, DTN-based routing protocols rely on a store-carry-forward strategy.

DTN routing protocols can be classified into three groups, namely (i) flooding-based [10], [11] where the number of packet replicas is not limited, (ii) quota-based [12], [13] where the number of replicas is limited, and (iii) forwarding-based [14], [15] where a single copy of a data packet is forwarded across the network until it reaches its destination. We expect a high delivery ratio of data packets under flooding-based protocols when the network resources such as buffer space are not limited. However, this results in overloading the network [12]. Also, it should be noted that in the case of low node density in the network (sparse network), this approach is not efficient in terms of delivery ratio as drones may have a limited opportunity to come within each other's communication range. The overhead of quota-based protocols, decreases but while delivery ratios in turn also decrease [16]. Unlike flooding-based and quota-based protocols that assume the network topology is not predictable or semi-predictable, forwarding-based protocols assume that network topology is predictable and can be modelled as a space and time graph. This implies that any change in the mobility pattern can significantly reduce the performance of these protocols. Considering all the aforementioned protocols and acknowledging that the drone network will be sparse and dynamic, we propose a novel forwarding-based protocol where the topology of the network is semi-predictable and tending to non-predictable. This is because drones may frequently change their mobility pattern due to changes in data delivery requests. The proposed protocol plans the flight path of the drone such that the nearby data packets' destinations are accommodated along the route to maximize the data delivery ratio while the drone is on its main mission to deliver the parcel to its destination.

The UAV path planning problem can also be categorized [17] as (i) off-line planning; where the global information about the waypoints is available in advance [18]–[22]. This is the most commonly used method, (ii) on-line planning; where the required information is partially known or completely unknown in advance [18], [20], [21], [23], [24], and (iii) cooperative planning; where a mission is too complex to be carried out by a single UAV and hence,

a group of UAVs are involved in planning [18], [19], [21], [25], [26]. The co-operative planning is often opted when the off-line planning is not feasible. The on-line planning, on the other hand, is not reliable because of the fast-changing nature of DTN. The DTN does not allow sufficient time and resources for the drone network to update global information appropriately. All of the three types of planning have been proven as NP-Complete [27]; however, the cooperative planning is considered most suitable in DTN driven by drone networks. This is because, we consider a divide and conquer approach through local optimization of the trajectories for each drone. The local optimization considers the energy consumption of each drones in its flight path; because UAVs have limited energy and their communications is considered as a significant source of power consumption. Hence, the planning needs to consider the energy limitation of the UAV [2]. The authors in [28] studied a similar problem and considered the closest waypoint strategy to identify the next waypoint at each step in consideration whether the UAV had enough energy to return to its home station. The authors used a greedy algorithm in planning, and it revealed that the planning needs to consider a number of other parameters than the shortest path. For instance, if a data packet has a limited time to live and a UAV arrives at a waypoint when the data packet expires, the delivery ratio of the network will decrease.

To address the said problem of UAVs' flight path planning in data communication, we explore the following hypothesis. Suppose that in a drone logistics network, every drone has a home station where a parcel is loaded onto the drone. Then, each drone plans the path directly towards the parcel's destination. For instance, as Figure 1(a) illustrates, the drone is loaded with four data packets to be delivered to destinations d_1 , d_2 , d_3 , and d_4 . As shown in Figure 1(b), the drone can plan a detour path to deliver the data while dropping off the parcel. However, the length of the detour path is limited by the energy budget of the drone. As drones may come within the communication range of each other, they can exchange the data packets. Hence, an optimal forwarding strategy is required. This is because drones plan the flight path according to packet arrivals. As illustrated in Figure 1(c), an appropriate forwarding strategy can exchange the packets between drones that increase their delivery ratio and reduce the delivery delay. This planning is to ensure that the parcel will be delivered before the deadline and the drones will have enough energy to return to their home stations. The key idea of our approach is to add a value-added service to a logistic network such as delivery UAVs.

Thus, we make the following contributions in this paper:

- We define the problem of finding a set of destinations for the drone to visit during its flight path. The objective is to exchange data packets between drones during their contact such that the data delivery delay is minimized and the delivery ratio is maximized. Drones have to drop off their packages before their deadline and return to their home stations such that the resulting journey does not exceed the drone's battery capacity.

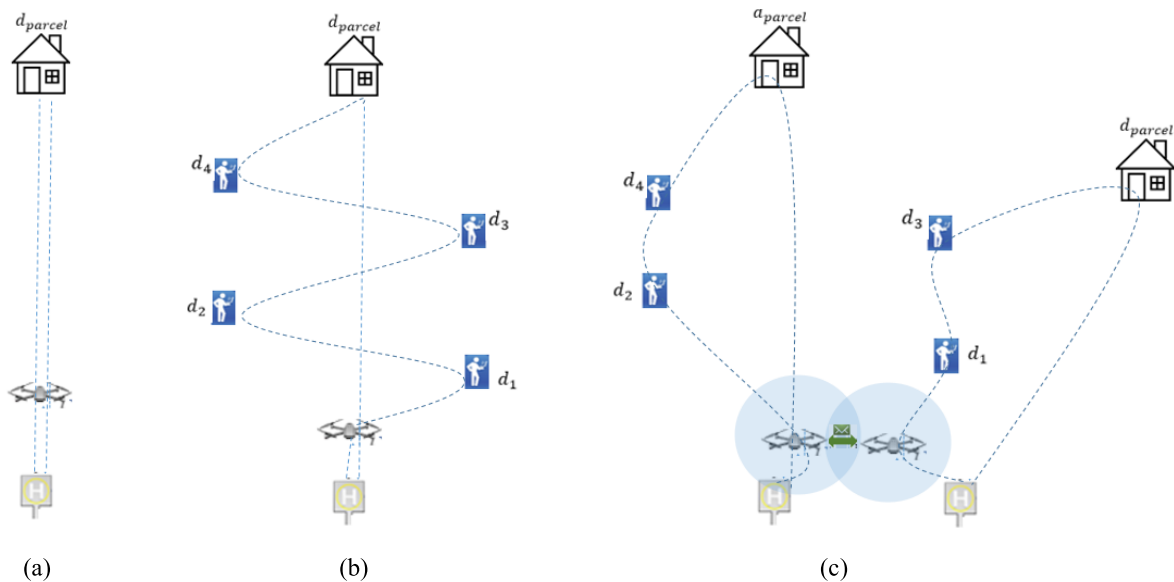


FIGURE 1. (a) Flight path planning for parcel delivery, (b) flight path planning for data and parcel delivery, (c) cooperative flight path planning for data and parcel delivery.

- We propose Weighted Flight Path Planning (WFPP), which is a heuristic algorithm that finds an optimal flight path that minimizes delivery delay and maximizes delivery ratio. WFPP assigns a weight to every data packet during a contact based on the packet's priority, time to live, and energy consumption level of the drone. Accordingly, the drones will add the destinations of the data packets with a high weight value to their path to satisfy the following two criteria: first, the parcel is delivered before the deadline. Second, the drones have enough battery to return to their home stations.
- We mathematically prove that proposed planning results in a high delivery ratio when drones visit the destinations of highly weighted data packets rather than visiting other destinations. Also, we calculate the ratio of the energy consumption between WFPP and the drone logistics network without data delivery.
- We compare the properties and effectiveness of WFPP against three algorithms; two well-known routing protocols namely Epidemic [10], and EBR [13] and a third flight planning algorithm [2] using a Java-based simulator called "ONE" [29]. The results show that WFPP delivers up to 25% more data packets as compared to the existing methods. Also, WFPP reduces data delivery delays by up to 66% while overhead ratio is low.

The remainder of this paper is organized as follows: Section II reviews methods that employ a routing algorithm in opportunistic networks and flight path planning for drones. Section III formulates the problem. In Section IV, we present WFPP and a detailed analysis of WFPP and the key properties. Finally, in Section V, we compare the performance of WFPP with well-known routing protocols and a movement path planning method before concluding in Section VI.

II. PROBLEM FORMULATION

Let us consider a logistics network of drones that are used by Amazon, UPS, and UberEATS to deliver data as an added feature to dropping off packages. Drones can communicate with each other and exchange data if they are within reception range. The objective is to determine a forwarding policy that optimizes the flight path planning but also guarantees parcel delivery within a given time and maximizes the data delivery ratio.

A. ASSUMPTIONS

Before describing the system, we first outline the following assumptions:

- 1- Each drone has an infinite buffer space to store data packets. This is justified as we are testing the routing algorithm performance only and not dropping policy which can impact network performance. Storage capacity has become so cheap that this assumption can also be considered realistic. In future work, we can investigate the dropping policy and buffer limitations.
- 2- Drones stay within the communication range of sources, destinations, and other drones until all forwarding packets are transferred. This can be done in a short contact duration as drones, due to their flight altitude, can bypass the obstacles which often prohibit line-of-sight communications. Hence, drones can collect and forward data with a maximum data speed.
- 3- Data packet and package destinations are registered in logistic companies, retailers and regulators, meaning that each drone is aware of the location of its destination. When you buy an item to be delivered, you provide the geographical address. This would be the same for the major data corporates such as Google, Azure, and

Alpine, if they transmit a large amount of traffic over drones that requires the location to be known to drones.

- 4- All the nodes communicate at 5G frequencies spectrum. Based on the Global System for Mobile Communications Association (GSMA), the frequencies of 26/40/50/66 GHz are supported for mobile devices.
- 5- Every drone moves independently which means every vehicle in a logistics company move independently with respect to the location of the item.

B. NOTATION

Consider a DTN with v drones represented by the set $N = \{n_1, \dots, n_v\}$ and q registered destinations including item buyers and data destinations indicated by $D = \{d_1, \dots, d_q\}$. Drones are responsible for picking up purchased items from m bases indicated by $B = \{b_1, \dots, b_m\}$ that belong to different retail or logistic companies and deliver them to the registered destination in D . Note, in this paper, we assume that when a drone returns to the base, there is always a parcel to pick up for delivery. Every drone during its flight, generates a data packet every T time unit. For every packet i in the network, the priority of μ_i is assigned by the source showing the importance of the data packet. We range the priorities from 1 to 10 respectively from low to high priority. Also, every packet i has time to live, T_i , that if it expires, the packet will be dropped from the buffer. Please note that the parcels delivery deadline is set when a drone is ready to pick it up.

Furthermore, drones consume energy when they fly and exchange data. To fly, drones need to overcome gravity, drag, and other weather conditions. Here we follow the formulation provided by [30] in calculating flight energy consumption. Drones also consume energy while sending and receiving data. Specifically, if drone i sends B bytes to any node $j \in (N \cup D)$, its energy consumption is (from [30]),

$$E_{send}(i, j) = B(\alpha_1 + \alpha_2 \times \varphi_{i,j}^\gamma) \quad (1)$$

where $\varphi_{i,j}$ is the physical distance between node i and j ($\varphi_{i,j} \leq R$) and α_1 is the energy consumption rate per forwarded byte. The energy consumption of the amplifier per byte is indicated by $\alpha_2 \times \varphi_{i,j}^\gamma$, where α_2 is the energy consumption factor of the amplifier circuit and γ is the path loss exponent, which ranges between two and four in Wi-Fi communication [31]. Moreover, in the case that drone i receives B bytes from any node $j \in N$, its energy consumption is [31],

$$E_{receive}(i, j) = B \times \vartheta \quad (2)$$

where ϑ is the energy consumption per received byte. As mentioned earlier, drones also consume energy to overcome gravity and drag forces due to forward motion and climate conditions. It should be noted that in a round trip, drones will have different energy consumption rates as in most of the cases drones have no package loaded on the return trip. This implies that drones consume lower power on their return trip. We calculate the energy consumption for a delivery trip of distance ξ (in meters) as follows:

$$E_{motion} = (e_{loaded} + e_{unloaded}) \xi \quad (3)$$

where e_{loaded} represents the power and velocity with the package present and without the package is indicated by $e_{unloaded}$. In other words, the total energy consumption of the outbound trip and the return trip is calculated.

Based on equations (1), (2), and (3), we extend the work in [30] and derive Equations 4 and 5 and calculate the remaining energy at time t as follows,

$$E_{current} = E_{max} - (E_{send} + E_{receive} + E_{motion}) \quad (4)$$

where E_{max} is the maximum capacity of a drone's battery. In other words, the current level of energy is updated based on the amount of sent and received data, and the travelled distance at any given time. Now, let us consider $\xi = 1$ meter as the minimum unit of distance in equation (3). Accordingly, the maximum length of travel, l_{max} , for a drone with the current power of $E_{current}$ is updated as follows:

$$l_{max} = \frac{E_{current} - E_{send}}{(e_{loaded} + e_{unloaded})} \quad (5)$$

where $E_{current}$ is the remaining energy of a drone. In other words, Equation (5) calculates the maximum distance that a drone can fly with respect to the current energy level, and the power for transmission and motion (assuming $\xi = 1$) at any given time t .

A drone starts its flight from a home base in B and returns to its starting point before it runs out of energy. Each drone has the geographical location of all other drones in D . We define a function called $H(i, D)$ that returns the distance from drone i to destinations in D . Specifically,

$$H(i, D) = \{h_{i,d_j} | \forall d_j \in D\} \quad (6)$$

where h_{i,d_j} is the Euclidean distance between drone i and d_j .

C. ENERGY EFFICIENT TRAVEL PATH

The objective is to find a flight path $M = m_0, m_1, m_2 \dots m_q, m_0$ where $m_0 \in B, m_i \neq 0 \in D$ such that the M is not longer than l_{max} and energy consumption of drones minimizes. Our algorithm is NP-hard by a reduction from a Travelling Salesman Problem (TSP) [32] which every drone finds the shortest possible route to visit the packets' destinations and return to the origin base. However, the minimum energy consumption occurs when drones' mobility model converges to the direct path towards parcel's destination. This is because the drone will not consume more energy due to detour for data delivery. Henceforth, in the following, we propose a novel heuristic algorithm to efficiently improve the packet exchange policy in order to achieve minimum energy consumption while maximizing delivery ratio and minimizing delivery delay.

III. WEIGHTED FLIGHT PATH PLANNING (WFPP)

In this section, we propose a heuristic method called **Weighted Flight Path Planning** (WFPP) that every drone weights the arrival packets based on the time to live, priority, and the power consumption of transmitting the packet. Then, the destination associated with the packet which has the highest weight added as the next waypoint to the modified

TSP solver to find the shortest flight route that visits each added destination and return to the origin base. As a constraint of this path planning, the drone should not run out of battery and the parcel should not be delivered late before arriving at the base. The outcome of this flight path planning results in the data network with high delivery ratio and minimum delivery delay.

In details, WFPP calculates the weight of a packet i based on μ_i , T_i , and the power consumption of transmitting the packet, E_{send} . Specifically,

$$\omega_i = \mu_i - (T_i + E_{send}) \quad (7)$$

Based on (7), when the time to live, T_i , decreases or energy, E_{send} , consumed for transmitting packet i reduces, the weight of the packet is increased. This implies that given a fixed priority, the weight is likely more if the information presents more demands. Hence, when a packet has short time to live, it increases its chance to be on a flight path. In other words, at each time that drones re-plan their flight path, the weight of packets increases as the time to live becomes shorter. The packet's priority is another parameter that affects the weight. As the priority of a packet indicates the importance of the packet, a higher priority results a higher weight. Note that, due to the different scales of said parameters, we utilize standard score [33] to normalize them which enables us to compare two scores that are from different normal distributions.

Algorithm 1 shows how this heuristic algorithm works when another drone comes within its range. It takes as input $G \subset D$ that is the destinations of packets, L_{max} as maximum length of flight for the drone, and consignment destination. It outputs a set of destinations as creates a path. Under WFPP, every drone first adds the origin base station and d_{parcel} that is the destination of loaded parcel (see line 6). Then, in lines 8–12, every drone adds the destination associated with the highest weighted packet. After that, WFPP calls our modified TSP solver which is the extended work of Christofides's heuristic [34] (see line 17) to return the cost of flight path for given destinations. If the flight path length is less than the maximum length of drone's flight L_{max} , the selected destination (lines 8–12) remains (see lines 18–25). However, if the time to live of a packet expires before arriving to the corresponding destination or the opposite drone can deliver it quicker, it is removed from the current drone's flight path (see line 20–23). Also, if the returned cost from TSP function is larger than L_{max} , the selected destination is removed from the flight path (see lines 26–30).

As discussed earlier, we also modified the TSP solver to ensure that the parcel is delivered before the deadline and the travel cost is not more than L_{max} . This is while in original TSP solvers, these constraints are not satisfied. This implies that parcel delivery always should be guaranteed to be conducted before the deadline. Moreover, Drones are guaranteed to have sufficient battery to return to the origin base. Hence, in the modified TSP solver, when the nearest destination of data is added as next destination, we compare the impact of such

Algorithm 1 Weighted Flight Path Planning

Input: $G, L_{max}, d_{consignment}$
Output: $M = m_0, m_1, m_2 \dots m_q, m_0 = \text{null}, m_0 \in B, m_{i \neq 0} \in D$

```

1  begin
2   $A_n = 0$ ; //counter for number of registered destinations
   added to the list of deliveries
3   $\omega_{max} = 0$ ; //maximum weight of registered destination
    $flag = 0$ ;
    $\aleph = -1$ ; //index for added registered destinations
4   $cost = 0$ ;
5   $mark = [false, false, \dots]$ ; //if a destination is added to
   route, the corresponding index in  $mark$  is true
    $remove = [false, false, \dots]$ ; // if a destination is
   removed from route, the corresponding index in  $remove$  is
   true
6   $M = M \cup m_0 \cup d_{parcel}; A_n ++$ ;
7  while  $A_n \leq |G|$  do
8    for  $i = 0$  to  $|G|$  do
9      if  $!mark(i) \ \&\& \ \omega_i > \omega_{max}$  then
10        $\aleph = i; \omega_{max} = \omega_i; flag = 1$ ;
11     end
12   end
13   if  $!flag$ 
14     break;
15   end
16    $mark(\aleph) = true; M = M \cup \aleph; A_n ++$ ;
17    $cost = TSP(M)$ ;
18   if  $cost \leq L_{max}$ 
19     for  $i = 0$  to  $|M|$  do
20     if  $\left[ T_i < \left( \frac{h_{j,m_i}}{S} \right) \ \&\& \ !mark(i) \right] \parallel \left( \frac{h_{opposit,m_i}}{S} \right) <$ 
    $\left( \frac{h_{current,m_i}}{S} \right)$ 
21        $remove(i) = true; mark(i) = false$ ;
22        $M = M - i; A_n --$ ;
23     end
24   end
25   end
26   if  $cost > L_{max}$ 
27      $M = M - \aleph; A_n --$ ;
28      $flag = 0; \omega_{max} = 0$ ;
29     Go to line 8
30   end
31 end

```

detour in delivery delay of the consignment. If the detour path causes overdue delivery for the parcel, the nearest data destination is removed from the route and is replaced with $d_{consignment}$. This way, we make sure that the parcel will be delivered before the deadline and that data destination will be added to the route after parcel delivery. Please note that the main objective is to deliver the parcel and as a value-added service, data delivery is conducted.

Let us consider the following scenario where drones n_1 and n_2 departed from b_2 and b_1 respectively. Figure 2 shows that

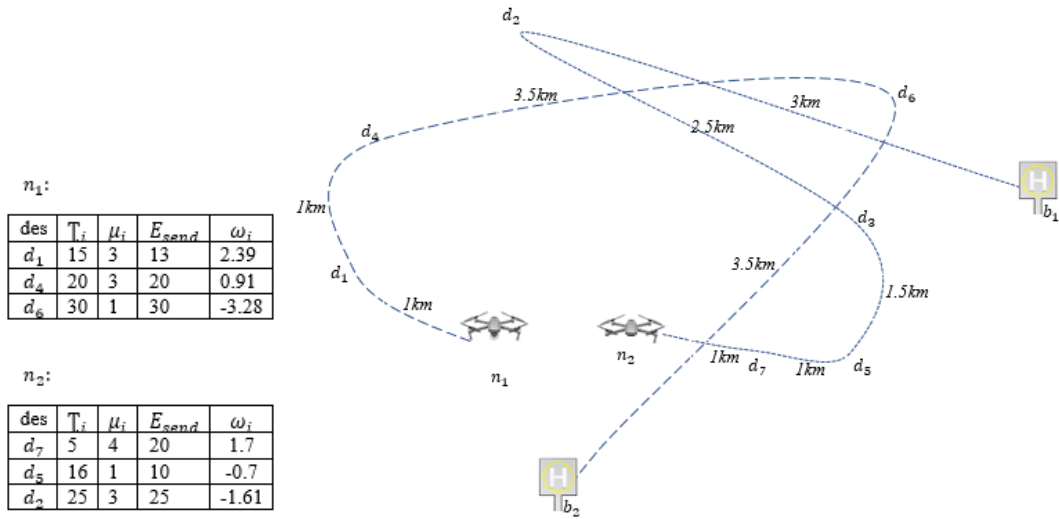


FIGURE 2. Original flight paths of two drones.

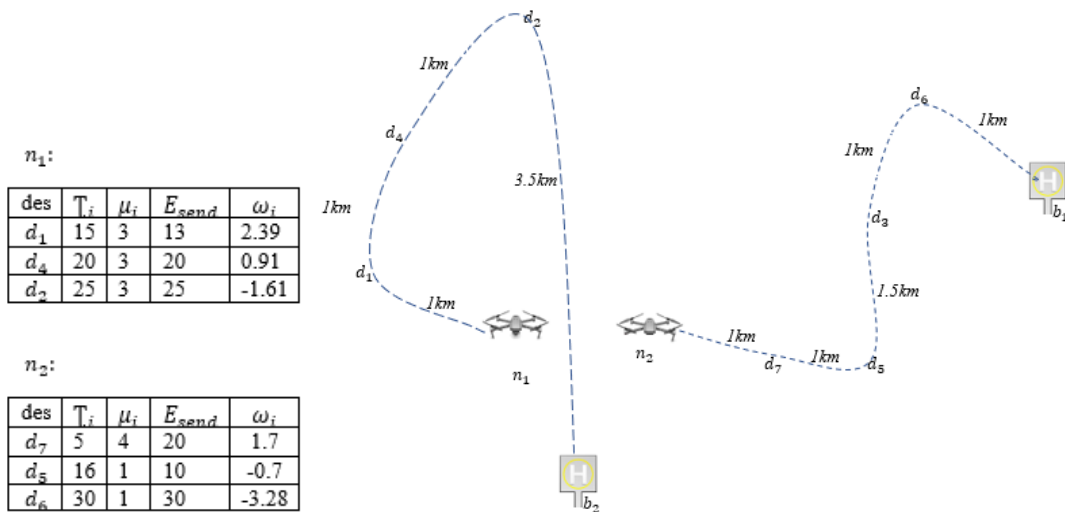


FIGURE 3. Optimized flight paths of the two drone in Figure 1 based on WFPP.

there are two drones n_1 and n_2 that carrying $\{d_1, d_4, d_6\}$ and $\{d_7, d_5, d_2\}$ respectively. The table in Figure 2 shows the time to live, energy usage, priority, and calculated weight of the corresponding packets. Each drone plans its path by adding the destination of most weighted packets. For example, n_1 is carrying a packet to be delivered in d_6 . However, d_6 is far away from the base and costs $3.5\text{km} (d_4 \text{ to } d_6) + 3.5\text{km} (d_6 \text{ to } b_2)$ flight to reach the base. Also, drone n_2 is carrying a packet to be delivered in d_2 that is far away from the base b_1 . As we see in Figure 3, when the two drones come within the communication range of each other, the packet with destination d_1 that has the maximum weight is involved in the modified TSP solver of both drones. The TSP's outcome reveals that the delivery delay is smaller if the packet with destination d_1 is carried by n_1 . This is because n_1 has a shorter distance to d_1 . The next destination selection by drones is d_7 with the weight of 1.7, that due to the shorter distance to n_2 , it will be added to its route. By completing the selection process, we see that

these drones only exchange two packets with destination d_2 and d_6 that results 2.5 km and 3.5 km less travel for drones n_1 and n_2 respectively.

We should also point out that the algorithm calculates the maximum length that a drone can fly. Hence, even if a drone can deliver a packet quicker but it may run out of battery, the packet's destination will not be included along the route. However, storing that packet increases the chance of its delivery as the drone will be getting closer to the destination and future forwarding opportunities can occur closer to that destination.

A. ANALYSIS

From the algorithms proposed in the previous section, we observe that the time complexity of WFPP algorithm is dependent on the number of TSP function calls to calculate a flight path that visits each added destination and return to the origin base. The worst case scenario is when the mark of all

destinations in G is True but not selected as waypoints of the route, which means our algorithm will iterate for $|G|$ times to check the possibility of adding waypoints into a flight path. After a destination in G is selected as a waypoint to be in the list of M , the algorithm again unmarks other destinations and restarts the search process (see lines 7-30). This implies that in a worse case, to add first waypoint n times TSP solver is called and for selecting the next way point $n-1$ calls, and so on. Specifically, in worse case, our algorithm runs the TSP function for a maximum of n^2 times:

$$O(n^2) = n + (n - 1) + \dots + 1; \quad \text{where } n = |G|$$

Therefore, the total time complexity of our algorithm is $O(n^2 \times O(TSP))$. Heuristic approaches to solve the TSP problem have different time complexities. For instance, Christofides's heuristic [34] has the time complexity of $O(n^3)$ that results in our algorithm with a complexity of $O(n^2 \times O(n^3)) = O(n^5)$.

We now prove that visiting the corresponding destinations (waypoints) of highly weighted packet results in the higher average delivery probability as compared with visiting any other destinations.

Theorem 1: Suppose that packets P and Q have the weight w_P and w_Q respectively. Visiting packet P 's destination increases the delivery ratio more than visiting packet Q 's destination, where $w_P > w_Q$.

Proof: Recall that the packet P has a time to live of \mathcal{T}_P that increases w_P if it is \mathcal{T}_P small (See Equation (7)). Therefore, assuming a fixed velocity of s for the drone, the Maximum Distance (MD_P) of flying to deliver the packet is,

$$MD_P = s \times \mathcal{T}_P \quad (8)$$

Similarly, for destination node Q that has a time to live of \mathcal{T}_Q , we have

$$MD_Q = s \times \mathcal{T}_Q \quad (9)$$

From (7), the weight of destination node P is $\omega_P = \mu_P - (\mathcal{T}_P + E_{send})$, and the weight of destination node Q is $\omega_Q = \mu_Q - (\mathcal{T}_Q + E_{send})$. We know that $w_P > w_Q$; therefore, it can be concluded that $MD_P < MD_Q$, which means selecting destination node P as the first destination, which has a higher weight than Q , leads to higher delivery ratio which is due to $\mathcal{T}_P < \mathcal{T}_Q$. ■

Theorem 2: Assume that the parcel's destination has the direct flight distance L from the current position of the drone, and the average distance between other waypoints along the detour flight path and the drone is k ; then, the maximum difference between the network energy consumption of WFPP with respect to the direct flight path from origin base to the parcel's destination is $\frac{L}{k(|G|-1)}$.

Proof: The network energy consumption when a drone visits only destination node P is,

$$E_{Network(P)} = (e_{loaded}) L \quad (10)$$

TABLE 1. Table of notations.

Notation	Description
d_i	Destination i
b_i	Base station i
μ_i	Priority of packet i
\mathcal{T}_i	Time to live of packet i
$E_{send}(i, j)$	Energy of transmission from i to j
$E_{receive}(i, j)$	Energy of receiving consumed by j
e_{loaded}	Energy of motion when drone is loaded
$e_{unloaded}$	Energy of motion when drone is unloaded
ξ	Distance in meter
e_{motion}	Energy of motion when drone is loaded and unloaded within the distance of ξ
$E_{current}$	Remaining energy
E_{max}	Maximum energy budget
l_{max}	Maximum length of travel
$H(i, D)$	Distance from drone i to destinations in D
h_{i,d_j}	Euclidean distance between drone i and d_j .
M	Flight path
ω_i	Weight of packet i

On the other hand, the minimum amount of energy consumed by visiting all destinations except destination P is,

$$E_{Network(|V|-1)} = (e_{loaded}) k \times (|G| - 1) \quad (11)$$

We are not considering the $e_{unloaded}$ in (10) and (11) because we assume that the drones will not take any detour path on their return to base. As a result, from (10) and (11), the ratio of energy consumption in WFPP in comparison to the optimal model is,

$$Ratio = \frac{(e_{loaded}) L}{(e_{loaded}) k (|G| - 1)} \quad (12)$$

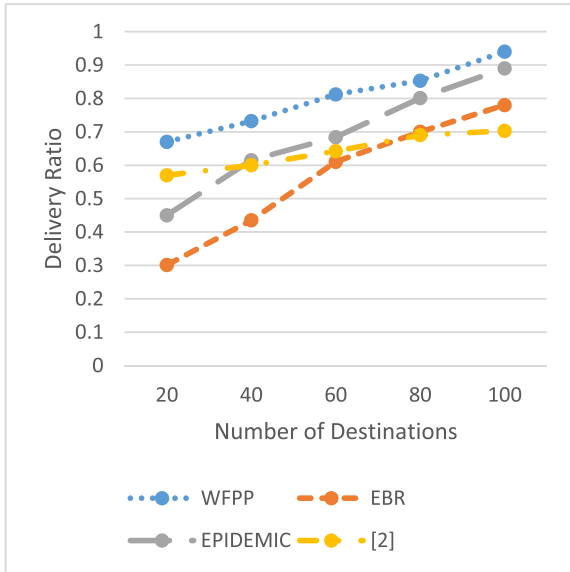
This is equal to,

$$Ratio = \frac{L}{k(|G| - 1)} \quad (13)$$

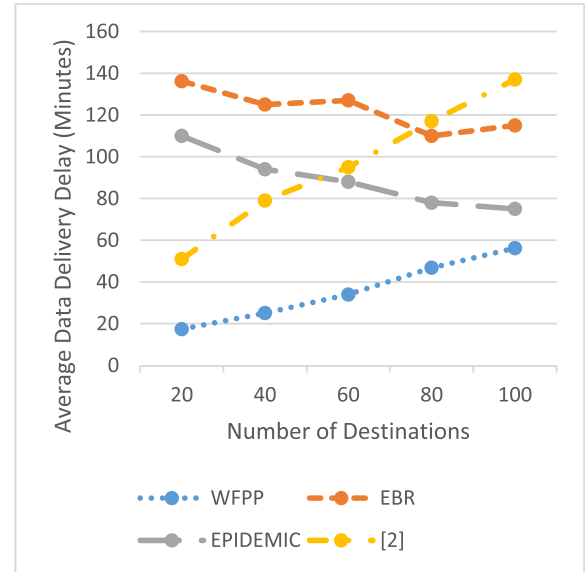
■

IV. EVALUATION

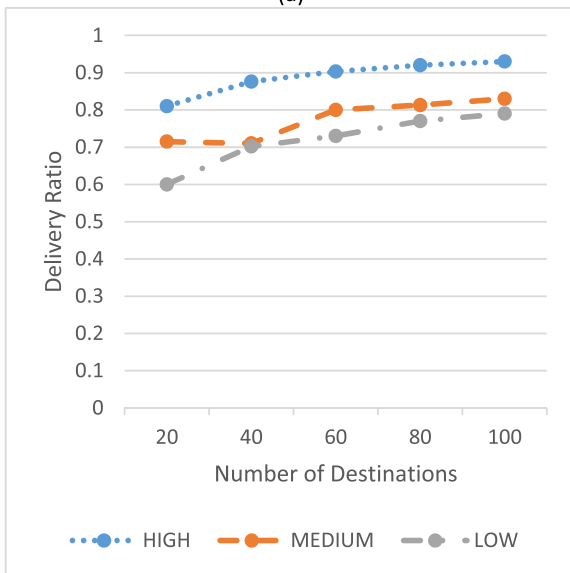
We compare WFPP to two DTN routing protocols called Epidemic [10] and EBR [13], and a similar path planning method [2], using a java-based simulator called "ONE" [29]. In the Epidemic routing protocol, packets are flooded throughout the network and in EBR, the number of replicas is limited and the replica are forwarded to nodes that frequently meet other nodes. In [2], a greedy search algorithm simply finds the closest next way point and establishes the flight path. In the simulations, we consider a disjointed network of drones that are placed randomly over a field of size $10 \times 10 \text{ km}^2$. We model the new generation of drones that have the capability of carrying up to a 5kg load. The weight of the drone with no load is 4.9 kg and moves at a speed of 100 km/h. Every drone has a battery with a capacity of 28000 mAh. Drones are equipped with GPS and a typical Wi-Fi using IEEE 802.11g with a radio range of 70 meters and the data transmission rate is set to 54 Mbps. We also assume that the geographical location of registered destinations is known to



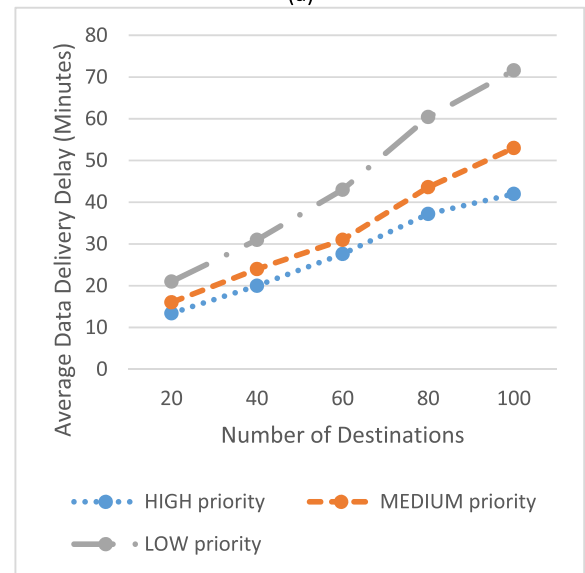
(a)



(a)



(b)



(b)

FIGURE 4. Delivery ratio of (a) comparable schemes, (b) WFPP based on the priorities, when number of destinations varies.

FIGURE 5. Average data delivery delay of (a) comparable schemes, (b) WFPP based on the priorities, when number of destinations varies.

all drones. Moreover, during a contact period, drones will stay in the communication range until the process of packet exchange is fully completed. Also, each drone generates a data packet with a different size every 60 seconds. This is because packet different in size, consume power differently for transmission.

In our evaluations, two groups of experiments are carried out. In the first experiment, the number of drones is limited to 100, and the number of registered destinations varies between 20 and 100. Please note a register destination can be both an item buyers and a data destination This impacts the performance of the network with same capacity. In the second experiment, the number of destinations is fixed to 50, and the number of drones varies between 50 and 250. This will give

us a very important insight of how increase in the number of drones for dropping of packages will impact on data network performance. We have achieved interesting results of this experiment. In all these scenarios, we assume different deadlines for consignment delivery to consider how it affects the flight path and the delay of data delivery.

We use the following metrics in our evaluation: (i) delivery ratio which is the ratio of the number of delivered packets to the number of generated packets, (ii) average data delivery delay which is the average delay that every delivered packet experience, (iii) overhead ratio which is ratio of number of delivered packets and number of relayed drones, (iv) average consignment delivery delay which is the average of time that a consignment is delivered, and (v) Energy Inefficiency which

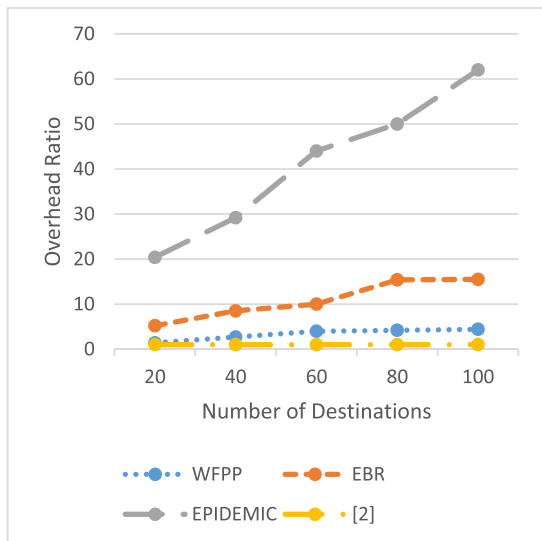


FIGURE 6. Overhead ratio of comparable schemes when number of destinations varies.

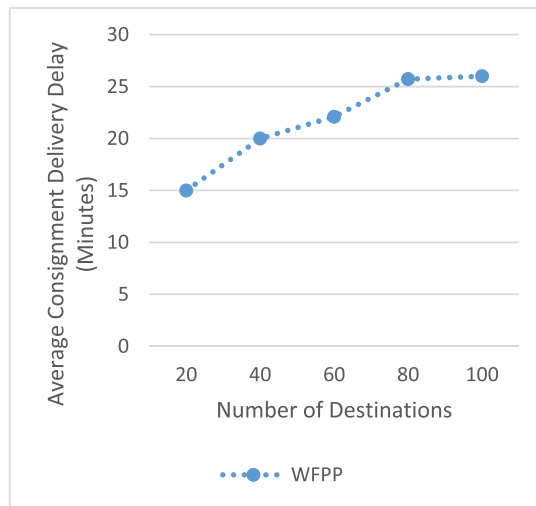
is the energy consumption’s difference between direct and detour distance. We also show how the priority of packets influences their delivery ratio and delivery delay.

A. EXPERIMENT ONE

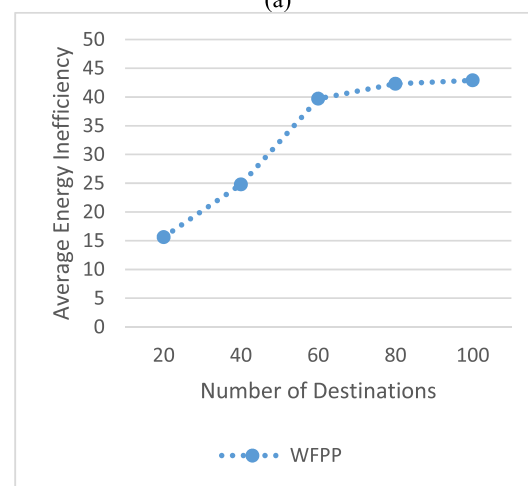
In this experiment group, the number of destinations varies from 20 to 100 and 100 drones are responsible to deliver their consignments and their generated data packets. Figure 4(a) shows that WFFP delivers up to 25% more packets compared with EBR, Epidemic, and [2]. This is because WFFP modifies its path in such a way that guarantees to deliver its buffered data packets unless the drone’s energy is not sufficient. However, the gap between WFFP and Epidemic reduces, while number of destinations growing. This is because the probability of drone’s contact increases that results in broadcasting more copies of packets throughout the network. Also, compared with the related work in [2], as they consider closest neighbor strategy, priority of data packets is not important. However, WFFP strategy is to set the drone’s path based on the priority of the packet, the time to live, and the energy consumption of delivering the packet that results in higher delivery ratio compared with low and medium priority (See Figure 4(b)).

From this observation, we can see in Figure 5(b) that WFFP delivers high priority packets up to 20% quicker. In general, figure 5(a) depicts that WFFP reduces delivery delays up to 66% compared with other methods. We see that the delay slightly increases by increasing the number of destinations and this is because more destinations will be added to the path that logically increases the delay. It should be noted that the proposed packet exchange policy brings the packets closer to their destinations whereas under EBR or Epidemic protocol, this is not necessarily true.

In terms of overhead ratio, figure 6 depicts that the proposed method in [2] has the minimum overhead as there is



(a)



(b)

FIGURE 7. (a) Average consignment delivery delay of WFFP, (b) energy inefficiency of WFFP, when number of destinations varies.

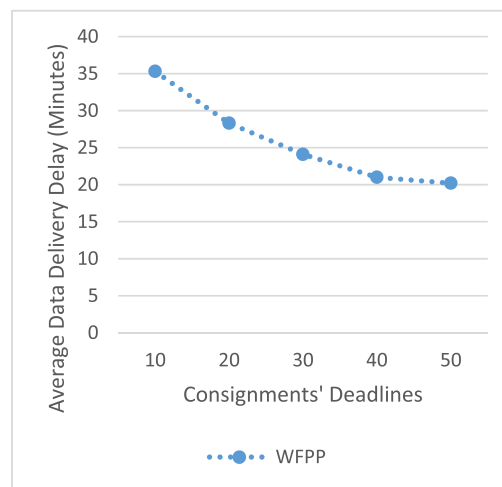
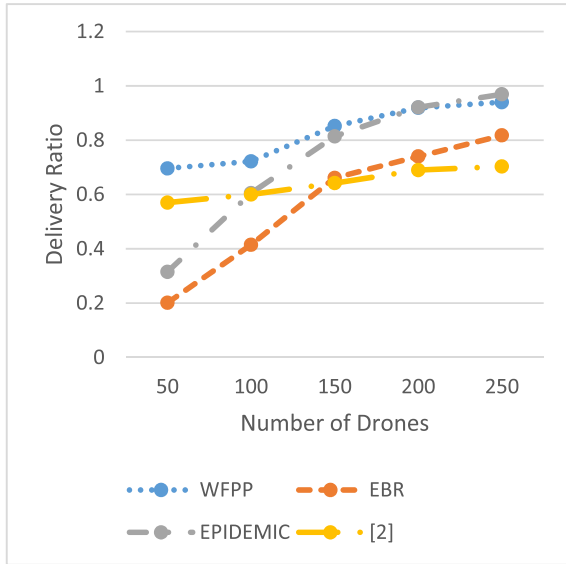
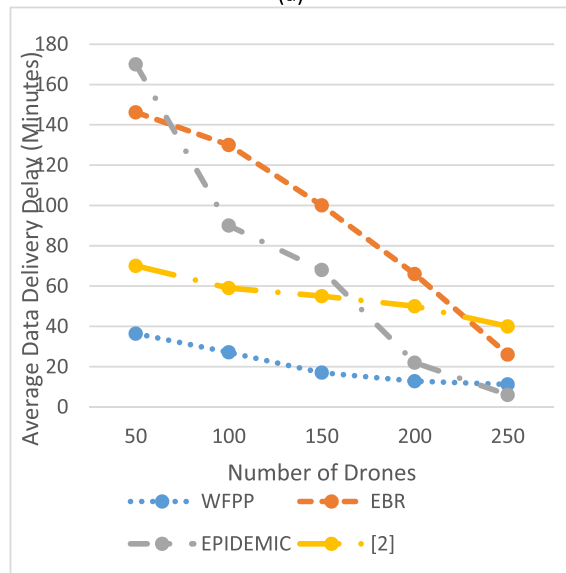


FIGURE 8. Average data packets delivery delay when consignments’ deadlines vary.

no communication between drones and consequently there is no collaboration between drones. Moreover, WFFP has



(a)



(b)

FIGURE 9. (a) Delivery ratio of comparable schemes, (b) average data delivery delay of comparable schemes, when number of drones varies.

up to 60% less overhead compared with EBR as it utilizes quota-based protocol. This is because under WFPP, at each time, only one copy of every packet exists in the network.

We also consider the impact of different number of destinations for data delivery on the consignment delivery delay. Figure 7(a) shows that when the number of destinations increases, the average delay of delivering the consignment increases up to 26 minutes which is very close to the maximum deadline (30 minutes). This is because of adding more destinations to the flight path before reaching to the consignment's destination. We also observe from figure 7(b) that by increasing the number of destinations, drones consume more energy as their detour path becomes longer. Please note that when the number of destination is small, drones

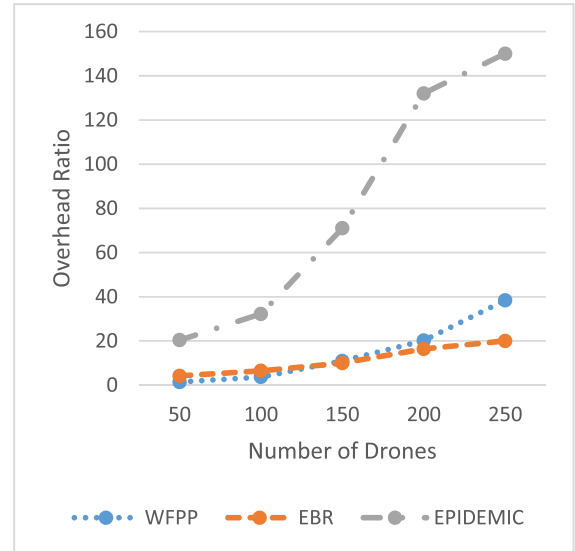


FIGURE 10. Overhead ratio of comparable schemes when number of drones varies.

are assumed frequently pick up parcels and deliver to those destinations. This implies that there is no idle drone that influences the average energy inefficacy metric. Even, in the case of having idle drones, they do not affect this metric. This is because they do not fly to have direct path or detour path. Lastly, we consider the impact of allocating varying consignment's deadlines on average data packets delivery delay (See Figure 8). We see that the data packets delivery delays decrease as the consignment's deadlines increase. This is due to the chance of being delivered before delivering the consignment. However, when the deadline is short, data packets will be delivered after delivering the consignment.

B. EXPERIMENT TWO

In this experiment group, the number of destinations is fixed to 50 and the number of drones varies from 50 to 250. Figure 9(a) shows that in terms of data delivery ratio, WFPP performs better than the comparable methods in low and high node density. As shown, by increasing the node density, Epidemic improves the delivery ratio logarithmically. This is because drones will have a higher chance to meet each other. Consequently, delays sharply reduce in high node density scenario (See Figure 9(b)). It is also clear that WFPP achieves minimum delay as shorter paths deliver the data packets quicker.

In terms of overhead, Figure 10 illustrates that WFPP has a low ratio, however, by increasing the number of nodes, the number of contact increases and the data packets will have more chance to be exchanged and become closer to the destination. Figure 11(a) shows that WFPP reduces the consignment delivery delay when the number of drones increases. This is because data packets will be quickly hosted at the best drone which is closer to the destination. Hence, drones will less likely modify their path frequently. This argument is

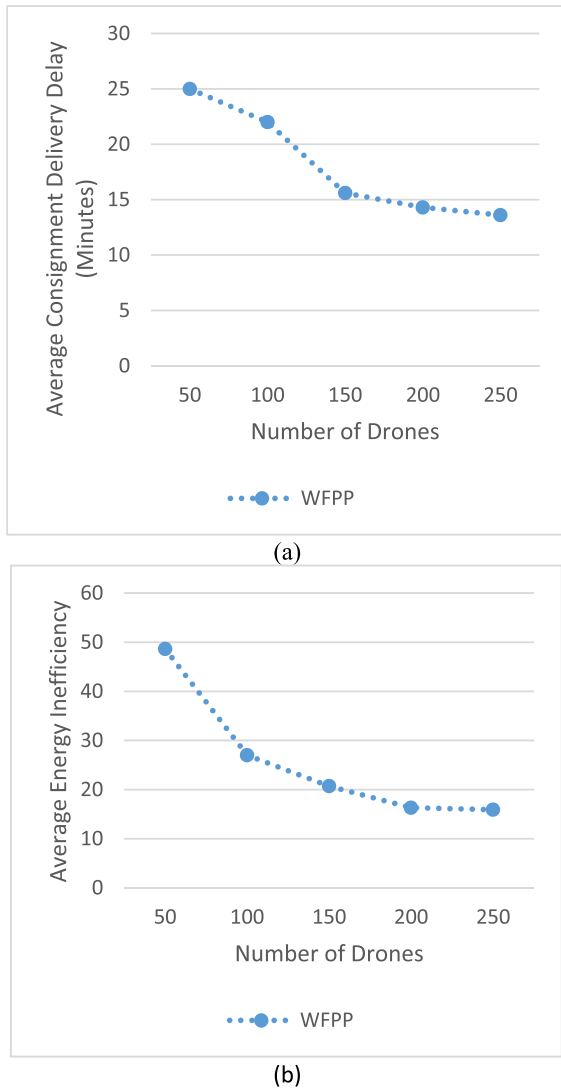


FIGURE 11. (a) Average consignment delivery delay, and (b) average energy inefficiency, of WFPP when number of drones varies.

proved by considering Figure 11(b) that shows in high node density, the average energy inefficiency sharply drops which is due to the establishing optimized path when data packets can be quickly hosted in the closest drone to the destination.

V. CONCLUSION

This paper presented a novel approach to intelligent transportation system and data communications where well-known retail companies such as Amazon, UPS and Dominos are focusing to add more services on their drone while dropping of the packages. Weighted Flight Path Planning (WFPP) considers the data packet's priority, time to live, and energy consumption for the transmission to weight them when they are in the exchange pool. Accordingly, the highly weighted packets are added to the flight path through a TSP solver. The results show that WFPP delivers up to 25% more packets against comparable methods. Also, WFPP reduces data delivery delays up to 66% while keeps the overhead in low ratio.

APPENDIX: LIST OF ABBREVIATIONS

Abbreviation	Meaning
DTN	Delay Tolerant Network
WFPP	Weighted Flight Path Planning
EBR	Encounter Based Routing
UAV	Unmanned Aerial Vehicles
UPS	United Parcel Service
ONE	Opportunistic Network Environment
TSP	Travelling Salesman Problem

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