Hybrid Device-to-Device and Device-to-Vehicle Networks for Energy-Efficient Emergency Communication

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Abstract: Considering the energy-efficient emergency response, subject to a given set of constraints on emergency communication networks (ECN), this article proposes a hybrid device-to-device (D2D) and device-to-vehicle (D2V) network for collecting and transmitting emergency information. First, we establish the D2D network from the perspective of complex networks by jointly determining the optimal network partition (ONP) and the temporary data caching centers (TDCC), and thus emergency data can be forwarded and cached in TDCCs. Second, based on the distribution of TDCCs, the D2V network is established by unmanned aerial vehicles (UAV)-based waypoint and motion planning, which saves the time for wireless transmission and aerial moving. Finally, the amount of time for emergency response and the total energy consumption are simultaneously minimized by a multiobjective evolutionary algorithm based on decomposition (MOEA/D), subject to a given set of minimum signal-to-interference-plus-noise ratio (SINR), number of UAVs, transmit power, and energy constraints. Simulation results show that the proposed method significantly improves response efficiency and reasonably controls system energy, thus overcoming limitations of existing ECNs. Therefore, this network can solve the key problems in rescue systems and make great contributions to post-disaster decision-making.

Index Terms: Emergency response, device-to-device (D2D), device-to-vehicle (D2V), unmanned aerial vehicle (UAV), complex networks, multiobjective evolutionary algorithm.

I. INTRODUCTION

The establishment of energy-efficient emergency communication networks (ECN) is one of key challenges in post-disaster rescue systems [1], which has a direct and strong influence on the safety of human beings, and the natural or ecological resources [2]. After natural or man-made disasters, most of ground devices (GD) can not access to congested or dysfunctional ground base stations (BS), and rescuers are blocked by

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collapsed terrains and can not enter sites immediately to collect real-time emergency information. Hence, to realize energy-efficient emergency response, it is necessary to establish ECNs, from which different types of communication links can benefit. As investigated in [3], widely used links mainly include device-to-device (D2D) and device-to-vehicle (D2V) links, through which users can transmit data toward rescue centers, i.e., the real-time collection and transmission of emergency information can be realized for post-disaster emergency response, and emergency centers can design reasonable rescue plans based on the collected emergency information. In [3], some potential network frameworks for emergency response were discussed, such as D2D communication networks, drone-aided communication networks, Internet of Things (IoT), etc. Nevertheless, it is still unclear how to jointly fuse heterogeneous networks and improve the performance of the fused networks [4].

A. Related Works and Motivation

D2D communication networks build dynamic point-to-point (P2P) links among users to improve the network connectivity, which shows strong advantages among uniformly distributed users. In [5], the D2D-based system (DBS) over long-term evolution (LTE) was designed to provide emergency services for mobile users, and the integrated framework for finding isolated users was designed in [6] and thus increased the D2D network lifetime. However, these works did not optimize wireless coverage. Following [5, 6], the LoRa-based ECN was proposed to overcome limitations of short-range D2D communication (e.g., WiFi and ZigBee [7]) [8]. To save total energy of users in need of emergency services, the D2D-aided messaging method was proposed in [9], but the network topology in these two works did not vary with time, which was not reasonable in real world. In [10], Wang et al. pointed out that some GDs were isolated because of terrestrial barriers (e.g., mountains or lakes) and could not access to public networks through existing D2D links.

Therefore, according to the sparsity of user distribution, it is impossible to establish D2D links for all users simultaneously, i.e., some users may be isolated, so other types of links should be explored to enhance the efficiency of emergency response. To this end, unmanned aerial vehicles (UAV)-based D2V links have provided some potential and effective solutions. In [11], the multi-armed bandit (MAB)-based D2V network was designed to serve users as many as possible. Following [11], Liu et al. deployed UAVs to increase the possibility of wireless access through D2V links [12]. To
maximize the wireless coverage of the D2V network, the circle packing theory-based method for deploying UAVs was proposed in [13]. In [14], the delay-optimal framework was proposed to partition the D2V network to ameliorate quality of service (QoS). Unfortunately, these works focused on wireless performance optimization, but did not take into account the energy constraints on systems. From the perspective of UAV performance, Mozaffari et al. reduced the hover time of drones and improved the spectrum efficiency simultaneously by optimal transport theory [15]. Following [15], the antenna array that consisted of multiple drones was designed to minimize the air-to-ground (A2G) transmission time by dynamically adjusting aerial attitudes of drones [16]. However, the balance between energy and efficiency was neglected. Especially, shortening emergency time is as important as saving system energy in emergency scenarios [17].

Given the previous works, we can know that just establishing D2D or D2V networks has some limitations, so it is worth studying how to effectively fuse heterogeneous networks and make full use of autonomous vehicles in dynamic emergency scenarios [18]. Unfortunately, the existing works in [2], [12], [19], and [20] did not synthetically solve the problem mentioned above. In [2], Zhao et al. scheduled UAVs to relay and fetch the data returned from existing D2D networks, but did not optimize D2D and D2V wireless transmission performance. To effectively recover post-disaster networks, the resource allocation system assisted by UAVs was proposed in [12], but it ignored the constraint on system energy limitations. Following [15], Arafat et al. established the UAV-assisted emergency network by particle swarm optimization (PSO) [19], and the non-orthogonal multiple access (NOMA)-based ECN was proposed in [20], but these two systems both did not consider the time cost of emergency response. Further, the authors in [21] also mentioned the necessity of fusing heterogeneous networks. Therefore, it is clear that most of works (e.g., [2], [5], [22]-[23]) just focus on one-layer optimization problem, namely, optimizing D2V links without D2D links and vice versa, and neglect the balance between time cost and energy consumption. To our best knowledge, this article is one of the first works on joint establishment, optimization, and fusion of D2D and D2V networks, subject to a set of signal-to-interference-plus-noise ratio (SINR), transmit power, number of UAVs, and energy constraints.

B. Contributions

Motivated by the above, we comprehensively study in this article an ECN aided by
D2D and D2V links, where a hybrid D2D and D2V network assisted by UAVs is proposed to realize the energy-efficient emergency response. Compared with the works in [2], [12], [19]-[23], this article considers the practical case that UAVs need to spend a large amount of time on approaching GDs, so the temporary data caching centers (TDCC) can be determined in advance before UAVs arrive. As a result, UAVs only need to fetch data returned from TDCCs rather than all GDs. Here, we aim to minimize the amount of time for emergency response and total energy consumption simultaneously by jointly establishing, optimizing, and fusing D2D and D2V networks, and the main contributions are summarized as follows.

- To tackle this problem, we first establish the D2D network from the perspective of complex networks by determining optimal network partition (ONP) and TDCCs. For D2D network segmentation, we propose a two-steps iterative algorithm by jointly maximizing the modularity and minimizing the outage probability of D2D links, subject to a given set of SINR and transmit power constraints. Based on the results of optimal network partition, we find out the TDCC in each network community that has the most powerful “connectivity” compared with the rest of members with the help of six measurements and Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) [24].

- Next, following the distribution of TDCCs, the D2V network is established by UAVs-based waypoint and motion planning. For the waypoint planning, we analytically determine the optimal waypoints of UAVs to reduce the amount of time for receiving emergency information returned from TDCCs by maximizing the ground-to-air (G2A) channel capacity. Next, given any two adjacent waypoints, the optimal control-based motion planning can significantly shorten the amount of time for aerial moving by dynamically adjusting the attitude of each UAV, subject to a set of environmental constraints.

- Finally, the amount of time for emergency response and the total energy consumption are optimized simultaneously by a multiobjective evolutionary algorithm based on decomposition (MOEA/D). Specifically, the first objective is to minimize the maximum time for conducting emergency tasks, and the second objective is to minimize the cumulative energy consumption, subject to a given set of minimum SINR, number of UAVs, GD transmit power, and total UAV energy constraints. It is notable that most of UAV energy is consumed by aerial motion compared with wireless
transmission, and the energy consumption of UAVs is much larger than that of GDs. By multiobjective optimization, the optimal solutions, namely, the optimal number of UAVs and the optimal GD transmit power, are selected from the Pareto Front (PF) by a knee node (KN)-based method. Numerical results show that the proposed method significantly saves the amount of time for emergency response and the total energy consumption compared with the existing works.

The remainder of this article is organized as follows. In Section II, we introduce the system model, including GD distribution, path loss, environment description, and problem formulation. In Section III, we first determine the ONP and the TDCCs, and then solve the optimal balance between time cost and energy consumption. The simulation results and discussions are presented in Section IV to evaluate the effectiveness of the proposed method, and the conclusions are drawn in Section V.

Notations: Scalars are denoted by italic letters, and vectors and matrices are denoted by bold-face lower-case and bold-face upper-case letters, respectively. For a directed graph, \( l_{i,k} = 1 \) if there is a link between GD \( i \) to GD \( k \) and \( l_{i,k} = 0 \) otherwise, but \( l_{i,k} \neq l_{i,k} \). \( \mathbb{N}(\cdot) \) denotes the minimum-maximum normalization. For a real-valued vector \( \mathbf{x} \), \( \|\mathbf{x}\| \) denotes its Euclidean norm. \( \mathbf{I}_{M \times M} \) denotes an identity matrix with size \( M \times M \), and \( \sim \) stands for “distributed as”. For a set \( \mathcal{X} \), \( |\mathcal{X}| \) denotes its cardinality.

Fig. 1. System model.

**II. SYSTEM MODEL AND PROBLEM FORMULATION**

**A. System Model**

The system consists of two units, including \( \mathcal{M} = \{1, \ldots, M\} \) aerial units (rotary wing UAV) and \( \mathcal{N} = \{1, \ldots, N\} \) ground units (GD equipped with sensors and communication modules). The GDs \( (x_i^{GD}, y_i^{GD}, z_i^{GD}), i \in \mathcal{N} \) are randomly distributed, and UAVs \( (x_j^{UAV}, y_j^{UAV}, z_j^{UAV}), j \in \mathcal{M} \) are dispatched to collect emergency data, as shown in Fig. 1. The D2D links are connected by jointly determining ONP and TDCCs, and the D2D
network can be divided into small communities, where each community has a TDCC (cluster-head) and GDs (members). Given the distribution of TDCCs, UAVs plan real-time trajectories to establish the D2V links so as to receive data returned from TDCCs, subject to a given set of transmit power, energy, and environment constraints. In our model, we assume that a control center located at an edge server (e.g., an emergency vehicle) can know the locations of GDs and UAVs, allocate spectrum resources between GDs and UAVs, and conduct computing tasks. The frequency-division multiple access (FDMA) over $O$ orthogonal channels is used for D2D (from GD to GD) and D2V (from GD to UAV) communication, where the carrier frequency is 433 MHz, the bandwidth is 1 MHz, and the upper bound of GD transmit power is denoted by $P_{\text{max}}^{\text{GD}}$. Clearly, the establishment of hybrid D2D and D2V networks is an alternative strategy for emergency response. To this end, we first introduce the GD distribution model, the path loss model, and the environment description.

In practice, a real-world D2D network can be abstracted as a graph [25], i.e., each GD has a certain probability to communicate with another device through the D2D link. In this article, Homogeneous Poisson Point Process (HPPP) is adopted to model the random graph ($\mathcal{G}$) over a digital elevation model (DEM), as shown in Algorithm 1. The computational complexity of Algorithm 1 depends on step 4-9, denoted by $O(N|\mathcal{D}|)$, where $\mathcal{D}$ is the set of DEM, and the degree distribution of $\mathcal{G}$ satisfies a Poisson distribution [26]. Especially, if some GDs are located in the remote area, their data will be transmitted through multi-hop D2D links and cached in TDCCs that wait for communicating with drones (see Fig. 1).

**Algorithm 1** Algorithm for Modeling GD Distribution

1: **Input**: Number of GDs $N$, Distribution Radius $r$, and Set of DEM $\mathcal{D}$
2: **Output**: ER random graph
3: **Initialize**: Number of iteration $N$ and $\mathcal{G} = \emptyset$
4: for $i = 1,2, \ldots, N$, do
5: Compute $u_i \sim \mathcal{U}(0,1)$, $\theta_i = 2\pi u_i$, and generate $(r, \theta_i)$
6: $(x_{i}^{\text{GD}}, y_{i}^{\text{GD}}) \leftarrow (r \cos(\theta_i), r \sin(\theta_i))$
7: Select two DEM points $(x_{m}^{\text{DEM}}, y_{m}^{\text{DEM}}, z_{m}^{\text{DEM}})$ and $(x_{n}^{\text{DEM}}, y_{n}^{\text{DEM}}, z_{n}^{\text{DEM}})$, $m,n \in \mathcal{D}$ by minimizing $\|x_{i}^{\text{GD}}, y_{i}^{\text{GD}}\| - \|x_{m}^{\text{DEM}}, y_{m}^{\text{DEM}}\|$ and $\|x_{i}^{\text{GD}}, y_{i}^{\text{GD}}\| - \|x_{n}^{\text{DEM}}, y_{n}^{\text{DEM}}\|$
8: Generate $z_{i}^{\text{GD}}$ by spatial bilinear interpolation (SBI), and add $(x_{i}^{\text{GD}}, y_{i}^{\text{GD}}, z_{i}^{\text{GD}})$ to $\mathcal{G}$
9: end for
10: return $\mathcal{G}$

To characterize different communication links, we adopt different channel models, which can reflect the influence of random attenuation caused by distances or obstacles.
For the D2D link, the free-space channel model is adopted [27]:

$$L_{i,k}^{\text{D2D}} = 10 \log_{10} \left( \frac{4\pi d_{i,k}}{G \lambda^4} \right)$$  \hspace{1cm} (1)

where $d_{i,k}$ is the distance between GD $i$ and GD $k$, $G$ is the path gain, and $\lambda$ is the wavelength. The D2V link includes line-of-sight (LoS) and non-light-of-sight (NLoS) links, and the probabilities of two links are respectively given by:

$$P_{\text{LoS}} = \frac{1}{1 + a \exp \left[ -b(\theta - a) \right]}, \quad \text{LoS link}$$
$$P_{\text{NLoS}} = 1 - P_{\text{LoS}}, \quad \text{NLoS link}$$  \hspace{1cm} (2)

where $a$ and $b$ are both constants, and $\theta$ is the elevation angle. Based on (1) and (2), the D2V channel model is expressed as follows [28]:

$$L_{i,j}^{\text{D2V}} = P_{\text{LoS}} \left[ 10 \log_{10} \left( \frac{4\pi d_{i,j}}{G \lambda^4} - \eta_{\text{LoS}} \right) \right] + P_{\text{NLoS}} \left[ 10 \log_{10} \left( \frac{4\pi d_{i,j}}{G \lambda^4} - \eta_{\text{NLoS}} \right) \right]$$  \hspace{1cm} (3)

where $d_{i,j}$ is the distance between GD $i$ and UAV $j$, and the additional path losses of LoS and NLoS links are $\eta_{\text{LoS}}$ and $\eta_{\text{NLoS}}$, respectively.

The environment description is a mathematical space restricting the topology of ECNs and the motion space of UAVs, which includes two aspects: 1) the terrestrial constraint and 2) the wind-field constraint.

Different terrain surfaces can cause changes to (1), so the D2D network topology is dynamic (see Section III-A). Moreover, to make sure that UAVs can safely fly along the collision-free trajectory [29], we add a DEM to our optimization model and express the terrestrial constraint as:

$$\left\| \left( x_{\text{UAV}}, y_{\text{UAV}}, z_{\text{UAV}} \right), \left( x_{\text{DEM}}, y_{\text{DEM}}, z_{\text{DEM}} \right) \right\| \geq \delta$$  \hspace{1cm} (4)

where $\delta$ is the buffer radius.

According to force analyses, a UAV is mainly affected by gravity, lift, and external forces. Particularly, the wind force has the strongest effect on UAV motion, so this article studies the influence of the wind-field on UAVs. To accurately model the wind-field over DEM, the Euler-based method is used to describe our wind-field [30], and the wind-speed vector, denoted by $\mathbf{f}$, is expressed as:

$$\mathbf{f} = \left[ d_{m,n} \frac{d_{m,n}}{\tan \theta}, \frac{h_{m,n}}{\tan \theta} \right], m,n \in \mathcal{D}$$  \hspace{1cm} (5)

where $\theta$ is the wind-speed direction. To guarantee that $\mathbf{f}$ can fit closely to terrestrial surfaces, we rotate $\mathbf{f}$ along $\mathbf{o} = \mathbf{f} \times \mathbf{f} \times \mathbf{z}$ by $\mathbf{R}$, where $\mathbf{f}'$ is the wind-speed vector next.
to \( \mathbf{f} \), and \( \mathbf{z} \) is the unit vector of \( z \)-axis in the earth frame, \( \theta_\mathbf{R} \) is the rotation angle, and 
\[
\mathbf{R} = \cos(\theta_\mathbf{R}) \mathbf{I}_{3,3} + \left(1 - \cos(\theta_\mathbf{R})\right) \mathbf{oo}^T + \sin(\theta_\mathbf{R}) \mathbf{\hat{z}}.
\]

**B. Problem Formulation**

Given the problem of establishing hybrid D2D and D2V networks, we can see that the main challenge is to jointly enhance the response efficiency of D2D and D2V networks. Thus, we define the problem from two parts. Specifically, we first evaluate the response efficiency of the D2D network by the number of TDCCs, because fewer TDCCs stand for better D2D link connectivity and can overcome limitations of UAVs, such as energy and communication distance constraints, i.e., fewer TDCCs yields higher response efficiency. Next, the amount of time for UAVs to fetch data returned from TDCCs can denote the response efficiency of the D2V network.

1) **Problem 1**

First, we model the D2D network as a weighted directed graph, denoted by \( \mathbf{G} = (\mathbf{V}, \mathbf{L}, \mathbf{W}) \), where \( \mathbf{V} \) is the matrix of GDs, \( \mathbf{L} \) is the adjacent matrix whose entry is \( l_{i,k} \), and \( \mathbf{W} \) is the weight matrix whose entry is the link weight, denoted by \( w_{i,k} \), and the connectivity of \( l_{i,k} \) is given by the outage probability \([31]\):

\[
\mathbb{P}_{\text{out}}(i,k) = \mathbb{P}\left(P_{i,k} / 10^{(\frac{R_{i,k}}{10})} \leq P_{\text{min}}\right) = 1 - \mathbb{Q}\left(\frac{P_{\text{min}} - P_{i,k} / 10^{(\frac{R_{i,k}}{10})}}{\sigma^2}\right)
\]

where \( P \) is the transmit power, \( P_{\text{min}} \) is the minimum received power, \( \sigma^2 \) is the standard deviation, and \( \mathbb{Q}(\cdot) \) is the Q-function that is defined as follows:

\[
\mathbb{Q}(x) = \int_x^\infty \frac{1}{\sqrt{2\pi}} e^{-y^2/2} dy
\]

Next, based on (6)-(7), \( l_{i,k} \) is given by:

\[
\begin{cases}
  l_{i,k} = 1, & \text{if } \mathbb{P}_{\text{out}}(i,k) \leq \varepsilon \\
  l_{i,k} = 0, & \text{otherwise}
\end{cases}
\]

where \( \varepsilon \) is the threshold of \( \mathbb{P}_{\text{out}} \), and \( w_{i,k} \) is expressed as follows:

\[
w_{i,k} = \mathcal{N}\left(\frac{\mu_{i,k}}{R_{i,k}}\right)
\]

where \( \mu \) is the packet size, and \( R \) is the capacity derived from \([31]\):

Consequently, we can define the problem of establishing the D2D network, denoted by \( P1 \), as follows:
\( \text{(P1):} \quad \min \ |T| \) \hspace{1cm} (10)

where \( T \) is the set of TDCCs.

2) Problem 2

Since TDCCs periodically return data, UAVs plan trajectories in real time to collect data effectively, subject to the environment and energy constraints. For simplicity, we define the problem of establishing the D2V network, denoted by \( \text{P2} \), as follows:

\[
\begin{align*}
\text{(P2):} & \quad \min \sum_{j \in M} T_j + T_i \approx T_j = (T_M + T_R)_j \\
& \quad \min \sum_{j \in M} E_j + E_i \approx E_j = (T_M P_M + T_R (P_R + P))_j \quad \text{s.t. } E_j \leq E_{\text{max}} \end{align*}
\]

(11)

where \( T_j \) and \( T_i \) denote the amount of emergency time of UAV \( j \) and GD \( i \), respectively, \( E_j \) and \( E_i \) denote the energy consumption of UAV \( j \) and GD \( i \), respectively, \( T_j \gg T_i \), \( E_j \gg E_i \), which are neglected for simplicity, \( T_M \) and \( T_R \) are the time for aerial motion and receiving data respectively, \( P_M \) is the motion power, \( P \) is the hovering power that is a constant [32], and \( E_{\text{max}} \) is the upper bound of UAV \( j \)'s energy.

Next, according to the kinematics, \( P_M \) is defined as:

\[ P_M = P_V + P_H \] \hspace{1cm} (12)

where \( P_V \) and \( P_H \) are the vertical and horizontal motion power, respectively. Thus, (12) is further given by [33]:

\[
\begin{align*}
P_V &= \begin{cases} 
\frac{mg}{2} v_V + \frac{mg}{2} \sqrt{v_V^2 + \frac{2mg}{\rho \pi r}}, & \text{climbing} \\
\frac{mg}{2} v_V - \frac{mg}{2} \sqrt{v_V^2 + \frac{2mg}{\rho \pi r}}, & \text{descending}
\end{cases} \\
P_H &= \frac{1}{2} \rho c_d A v_H^3 + \frac{\pi}{4} N_b c_b \rho c_d \omega^3 r^4 \left( 1 + 3 \frac{v_H}{\omega r} \right) + \omega m \rho g \times \alpha
\end{align*}
\]

(13)

where \( v_V \) and \( v_H \) are the vertical and horizontal velocities, respectively, \( c_d \) is the drag coefficient, \( c_b \) is the blade chord, \( N_b \) is the number of blades, and \( \alpha \) can be solved by:

\[
2 \pi \rho \omega^2 r^4 \alpha \sqrt{\frac{v_H^3}{\omega^2 r^2} + \alpha^2} - mg = 0
\]

(14)

where \( \rho \) is the air density, \( r \) is the rotor disk radius, and \( m \) is the mass.

III. HYBRID D2D AND D2V NETWORKS

In this section, we first solve (P1) to establish the D2D network by solving ONP and determining TDCCs. Next, according to the distribution of TDCCs derived from key
nodes detection, we establish the UAV-aided D2V network by solving (P2) with the help of convex optimization and multiobjective optimization.

A. D2D Network Establishment

To stably collect and transmit emergency information, the main target is to design the D2D network by solving (P1), including network establishment and optimization, and to guarantee that GD data can be forwarded toward and cached in TDCCs, which can significantly improve the energy efficiency by saving the time and the energy of emergency response. Generally, establishing a D2D network is a polynomial problem (PP), but if we want to optimize such network, PP will become a non-polynomial problem (NPP). It is quite difficult to solve (P1) directly, so we propose an iterative method, i.e., we decompose (P1) into two subsections. In the first subsection, given the current D2D network topology, we optimize the community division of the D2D network. In the second subsection, we optimize the wireless transmission performance, which transforms the network topology. Finally, by iterating the above two steps, ONP can be obtained.

1) Optimal Network Partition

We assert from (P1) that minimizing (P1) is equivalent to the optimal community division, and can be realized by maximizing the modularity, denoted by $Q$, so the objective function can be defined as [34]:

$$
\text{(P1-a): } \max Q
$$

where $Q$ is always larger than 0, and larger $Q$ indicates better community division [35].

In [36], the general modularity is expressed as follows:

$$
\max \frac{1}{2|N|\langle D \rangle} \sum_{i \in N} \sum_{k \in N} \left( I_{i,k} - \frac{D_{i,k}}{2|N|\langle D \rangle} \right) \mathbb{I}(c_i, c_k)
$$

where $c$ is the community label, and $\mathbb{I}()$ is the symbol function:

$$
\mathbb{I}(c_i, c_k) = \begin{cases} 
1, & \text{if } c_i = c_k \\
0, & \text{otherwise}
\end{cases}
$$

Based on our proposed model, denoted by $G$, we extend (17) as follows:

$$
\max \frac{1}{W} \sum_{i \in N} \sum_{k \in N} \left( w_{i,k} - \frac{w_{i,k}^{in} w_{i,k}^{out}}{W} \right) \mathbb{I}(c_i, c_k)
$$

where $W = \sum_{i \in N} \sum_{k \in N} I_{i,k} w_{i,k}$ is the sum of weights, $w_{i,k}^{in} = \sum_{k \in N} I_{i,j} w_{k,j}$ is the in-weight, and $w_{i,k}^{out} = \sum_{i \in N} I_{i,j} w_{i,k}$ is the out-weight.
**Proposition 1:** Maximizing (18) is equivalent to optimizing the label vector $s$:

$$s = [s_1, ..., s_i], i \in \mathcal{N}$$

(19)

where $s_i$ is equal to $+1$ or $-1$, which meets $\sum_{i \in \mathcal{N}} (s_i)^2 = |\mathcal{N}|$.

**Proof:** First, we rewrite (18) as the following compact form:

$$\max \frac{1}{4W} s^T (B + B^T) s$$

(20)

where $B$ is the modularity matrix whose entry is equal to $w_{i,k} - \frac{w^i_k w^k}{W}$, and $\mathbb{I}(c_i, c_k) = \frac{1}{2}(s_is_k + 1)$.

Next, the Singular Value Decomposition (SVD) is used to decompose $B + B^T$:

$$B + B^T = USV^T$$

(21)

where $S$ is the singular value matrix whose entry equals $\sqrt{\beta_i}$, $\beta_i$ is the eigenvalue of $(B + B^T)(B + B^T)^T$. $B + B^T$ is a square matrix, i.e., $U = V$, so (21) is expressed as:

$$\max \frac{1}{4W} s^T PS'P s$$

(22)

where $S'$ consists of the eigenvalue of $B + B^T$, denoted by $b$, that is placed along the diagonal of $S'$, and $P$ consists of the eigenvector of $B + B^T$, denoted by $v$. Therefore, (23) is simplified as:

$$\max \frac{1}{4W} \sum_{i \in \mathcal{N}} b_i (v_i^T s)^2$$

(23)

Finally, to maximize (23), we optimize the value of $v_i^T s$ by paralleling $v_i^T$ to $s$ as close as possible, i.e., if $v_i^T$ is perpendicular to $s$, $v_i^T s$ is equal to 0. Thus, by sorting $b_i$, in decreasing order ($b_1 \geq ... \geq b_i \geq ... \geq b_N$), we can know that if $v_{i,j} > 0, \forall v_{i,j} \in v_i^T$, $s_i \in s$ is equal to $+1$, and $-1$ otherwise. Clearly, (23) proves the proposition.

Following Proposition 1, the bisection-based algorithm is proposed to determine ONP, as shown in Fig. 2, and the detailed steps are listed in Algorithm 2:

- Assume that all GDs belong to the same community initially.
- Update the label vector $s$ by Proposition 1.
- Compute $\Delta Q = \frac{1}{4W} (s')^T (B_{g} + B_{g}^T)(s')$, where $g$ is the subgraph of $G$, $B_{g}$ is the submatrix of $B$, and $s'$ is the subvector of $s$, and update ONP by $\Delta Q$. 


Algorithm 2: Algorithm for Community Division

1: **Input:** Weighted Directed Graph $G = (V, L, W)$
2: **Output:** Set of Communities
3: **Initialize:** $C = \{c_1\}$, and label vector $s = [0 \ldots 0]^T$
4: for $c_i \in C$ do
5: Compute $Q(c_i)$ based on the unit label vector $[1 \ldots 1]^T$,
6: Compute $S'$ of $B + B^T$, and generate $b_i$ and $v_i$ by sorting $b_i$ in decreasing order
7: for $v_i, j \in V_i$ do
8: if $v_i, j \leq 0$ then
9: $s_j = -1$
10: end if
11: end for
12: Compute $\Delta Q = \frac{1}{4W}(s')^T(B_s + B_s^T)s'$
13: if $\Delta Q > 0$ then
14: Remove $c_i$ from $C$, and add two new communities to $C$ based on $s_j$ in $s$
15: end if
16: end for
17: return $C$

As illustrated in [25], the large positive modularity indicates when a statistically surprising fraction of the edges in the network fall within the same community. Thus, we need to optimize the outage probability between GDs so that GDs can communicate with each other, i.e., we need to make GDs belong to the same community as far as possible. Hence, the optimization problem is defined as:

$$(P1-b): \quad \min \sum_{i \in N} \sum_{k \in N} 1 - \Omega \left( \frac{P_{ \min } - P_{i,k}}{10^{\frac{b_{i,k}^2}{\sigma^2}}} \right)$$

(24)

**Proposition 2:** Minimizing (24) is equivalent to optimizing $P$.

**Proof:** First, we regard $P$ in (24) as a variable and determine its first derivative:

$$\frac{dQ}{dP} = -\left( \frac{1}{\sqrt{2\pi}} e^{-s^2/2} \right) \left[ \left. \frac{d}{dP} \left( \frac{P_{ \min } - P_{i,k}}{10^{\frac{b_{i,k}^2}{\sigma^2}}} \right) \right|_{s=0} \right] dP = \frac{1}{\sqrt{2\pi} \sigma^2} e^{-\left( \frac{P_{ \min } - P_{i,k}}{10^{\frac{b_{i,k}^2}{\sigma^2}}} \right)^2} < 0$$

(25)

Based on the result of (25), we know that (24) is a monotone decreasing function in
its domain, i.e., minimizing (24) is equivalent to maximizing the variable $P$:

$$\max P_{i,k}$$

s.t. $$\gamma \leq \frac{P_{i,k}/10^{(d_{ki}^2/10)}}{N_0 + \sum_{l \in \mathcal{L} \setminus i} P_{l,k}/10^{(d_{kl}^2/10)}},$$

(26)

where $\mathcal{L}$ is the set of GDs that connect with the GD $k$, $N_0$ is the noise power, $\gamma$ is the threshold of SINR, and the optimal SINR of GD $i$ satisfies:

$$\frac{P_{i,k}/10^{(d_{ki}^2/10)}}{N_0 + \sum_{l \in \mathcal{L} \setminus i} P_{l,k}/10^{(d_{kl}^2/10)}} \leq P_{i,k} \leq P_{\max GD}^{GD}$$

(27)

Therefore, to jointly reduce the interference power and obtain optimal SINR, the optimal $P_{i,k}$ is equal to

$$P_{\min} 10^{(d_{ki}^2/10)},$$

i.e., GD $i$ can not transmit data with its maximum transmit power so as to reduce its interference to other GDs. Clearly, (25)-(27) prove the proposition.

By iterating the following two steps, (P1) can be solved, i.e., the minimum of $|T|$ equals the optimal number of communities, as shown in Algorithm 4.

- Given the fixed network topology, we can solve the sub-optimal modularity (P1-a) by optimizing the network partition, as shown in Algorithm 2.
- By optimizing the outage probability (P1-b), the network topology is updated by improving the connectivity of GDs, as shown in Algorithm 3.

---

**Algorithm 3** Algorithm for Updating Network Topology

1: **Input:** Weighted Directed Graph $G$, Number of GDs $N$, and GD Transmit Power $P$
2: **Output:** Updated Weighted Directed Graph $G$
3: **Initialize:** Number of iteration $N$
4: **for** $i = 1, 2, \ldots, N$ **do**
5:  **for** $k = 1, 2, \ldots, N$ **do**
6:    Update $P_{i,k}$ based on (1) and (27)
7:  **Update** $P_{\text{out}}(i,k)$ based on (6)
8:  **Update** $l_{i,k}$ and $w_{i,k}$ in $G$ based on (8) and (9), respectively
9: **end for**
10: **end for**
11: return $G$

---

**Algorithm 4** Algorithm for ONP

1: **Input:** Weighted Directed Graph $G$, Number of iteration $N$, and Accuracy Threshold $\ell$
2: **Output:** Set of Communities $\mathcal{C}$
3: **Initialize:** Initial modularity $Q_0$ and initial set of communities $C_0$
4: **for** $i = 1, 2, \ldots, N$ **do**
5: Update $G$ based on Algorithm 3
6: Update $C_i$ based on Algorithm 2, and compute $Q_i$
7: if $|Q_0 - Q_i| \leq \ell$ or $i = N$ then
8:     return $C_i$
9: end if
10: $Q_0 = Q_i$
11: end for
12: return $C_i$

The computational complexity of Algorithm 2 equals to $O(|C||V_i^T|)$. Similarly, the computational complexity of Algorithm 3 is denoted by $O\left( N^2 \right)$, where $N$ is the number of iteration. For Algorithm 4, it can be regarded as the integration of Algorithm 2-3, so its computational complexity depends on step 4-10, denoted by $O\left( |C||V_i^T|N^3 \right)$.

2) Optimal Solution of P1

According to ONP derived from Algorithm 4, we need to determine TDCCs in all communities that can receive and cache data returned from community members, which can jointly save the energy consumption of UAVs and shorten the amount time for emergency response, i.e., UAVs only need to fetch data from TDCCs without traversing all GDs. In this article, six measurements are selected, including in-degree centrality (IC), out-degree centrality (OC), clustering coefficient (CC), closeness centrality (cc), betweenness centrality (BC), and eigenevtor centrality (EC).

Specifically, IC representing the “popularity” of GD $i$ is defined as:

$$\text{IC}(i) = \sum_{k \in N} I_{i,k} / (|N| - 1)$$

(28)

Similarly, OC is expressed as follows:

$$\text{OC}(i) = \sum_{k \in N} I_{i,k} / (|N| - 1)$$

(29)

The transitivity of GD $i$ is given by CC [37]:

$$\text{CC}(i) = \frac{\sum_{k \in N} \sum_{l \in N} \left( I_{i,k} W_{i,l} \right)^{\Theta} \left( I_{i,l} W_{i,k} \right)^{\Theta} \left( I_{i,k} W_{i,l} \right)^{\Theta}}{\left( \sum_{k \in N} I_{i,k} + \sum_{l \in N} I_{i,l} \right) \left( \sum_{k \in N} I_{i,k} + \sum_{l \in N} I_{i,l} - 1 \right)}$$

(30)

Then, cc is used to accurately evaluate the proximity among GDs:

$$\text{cc}(i) = (|N| - 1) / \sum_{k \in N} U_{i,k}$$

(31)

where $U_{i,k}$ is the shortest path (SP) between GD $i$ and GD $k$. To solve $U_{i,k}$, Dijkstra algorithm is one of the most useful methods [38], where the path cost is expressed as $W_{i,k}$, which works as a routing protocol to find the path between GDs and TDCCs.
The ability of information dissemination is given by BC:

\[
BC(i) = \sum_{k \in N} \sum_{l \in N} \frac{\mu_{k,l}(i)}{\sum_{l \in N} u_{k,l}}
\]  
(32)

where \( \mu_{k,l}(i) \) is the number of SPs that pass through the GD \( i \).

EC is the comprehensive measurement that evaluates the importance of GD \( i \) [39]:

\[
EC(i) = w^* \sum_{l \in N} l_{i,k} e_k
\]  
(33)

where \( w^* \) is the reciprocal of the maximum eigenvalue of \( W \), and \( e_k \) is the element of the eigenvector according to \( (w^*)^{-1} \).

Thus, (28)-(33) are input into TOPSIS to determine TDCCs, including five steps.

**Step1**: Build the evaluation matrix, denoted by \( X_{M \times N} \), for a community, where \( M \) is the number of GDs in each community, and \( N \) is equal to 6. To solve the scalar effect, \( X \) is standardized as follows:

\[
x'_{m,n} = \frac{x_{m,n}}{\sqrt{\sum_{m=1}^{M} x_{m,n}^2}}, x_{m,n} \in X
\]  
(34)

**Step2**: The weight of measurement \( n \), denoted by \( \omega_n \), is obtained by the entropy-based method, and the standardized weight matrix \( Y \) is expressed as follows:

\[
\omega_n = \frac{1 + \sum_{m=1}^{M} (x'_{m,n} \ln x'_{m,n}) / \ln m}{\sqrt{\sum_{n=1}^{N} (1 + \sum_{m=1}^{M} (x'_{m,n} \ln x'_{m,n}) / \ln m)^2}}
\]  
(35)

\[
Y = \begin{bmatrix}
x'_{1,1} & \ldots & x'_{1,n} \\
\vdots & \ddots & \vdots \\
x'_{m,1} & \ldots & x'_{m,n}
\end{bmatrix}\begin{bmatrix}
\omega_1 \\
\vdots \\
\omega_N
\end{bmatrix}
\]  
(36)

**Step3**: Respectively determine the set of positive solutions, denoted by \( S^+ = \{ \max \{ y_{1,1}, \ldots, y_{m,1} \}, \ldots, \max \{ y_{1,n}, \ldots, y_{m,n} \} \} \), and the set of negative solutions, denoted by \( S^- = \{ \min \{ y_{1,1}, \ldots, y_{m,1} \}, \ldots, \min \{ y_{1,n}, \ldots, y_{m,n} \} \} \).

**Step4**: Let \( D^+_m = \sqrt{\sum_{n=1}^{N} (S^+_{n} - y_{m,n})^2} \), \( S^+_n \in S^+ \) and \( D^-_m = \sqrt{\sum_{n=1}^{N} (S^-_{n} - y_{m,n})^2} \), \( S^-_n \in S^- \).

**Step5**: The importance of each GD is evaluated by \( \frac{D^-_m}{D^-_m + D^+_m} \in [0,1] \).

It is notable that once TDCCs are determined, their members in communities only forward data toward TDCCs.
B. D2V Network Establishment

To effectively collect and transmit emergency data, only establishing D2D networks is not enough, because there exist some isolated GDs that are located in the remote area or blocked by terrestrial constraints. Therefore, the UAV-aided D2V network can overcome the above limitations. In this section, we first determine the optimal UAV deployment. Next, following the framework we proposed in [23], we describe (P2) as a multiobjective optimization problem (MOP) and solve it by MOEA/D.

1) Optimal UAV Deployment

Based on the framework we proposed in [23], the D2V link can be established by two parts, including waypoint planning and motion planning, i.e, a real UAV trajectory consists of waypoints and paths. Therefore, we first determine the optimal waypoints for UAVs by optimizing $T_R$ in (P2). Next, based on the optimal waypoints, the motion planning can optimize $T_M$ in (P2), subject to a given set of energy and environmental constraints on UAVs.

To effectively shorten the amount of time for transmitting data, we need to maximize the G2A channel capacity, i.e., minimize $T_R$:

$$\text{(P2-a): } \max B \log_2 \left( 1 + \frac{P_{i,j} / 10^{(G_{10})}}{N_0 + \sum_{k \in S_i} P_{k,j} / 10^{(G_{10})}} \right)$$

where $S_i$ is the set of TDCCs allocated to the UAV $j$, and $B$ is the bandwidth.

From (37), we can divide (P2-a) into two subproblems, including maximizing the UAV received power and minimizing the GD interference power:

$$\max P_{i,j} / 10^{(G_{10})}$$

s.t. $P_{\min} 10^{(G_{10})} \leq P_{i,j} \leq P_{\max}$

$$\min \sum_{k \in S_i} P_{k,j} / 10^{(G_{10})}$$

s.t. $P_{\min} 10^{(G_{10})} \leq P_{k,j} \leq P_{\max}$

Here, from (38) and (39), we can find that it is easy to optimize $P$ directly, because the function of $P$ is monotone in its domain. Then, we need to optimize G2A path loss.

By simplification, we can first define the optimization problem as follows:

$$\min \frac{(\eta_{\text{NLoS}} - \eta_{\text{LoS}})}{1 + a \exp \left[ -b \left( \arcsin \left( \frac{h_{i,j}}{d_{i,j}} \right) - a \right) \right]} + \left( 10 \log_{10} \frac{(4\pi d_{i,j})^2}{G\lambda^2} - \eta_{\text{NLoS}} \right)$$

(40)
where \( h_{i,j} = z_{i,j}^{\text{UAV}} - z_{i,j}^{\text{GD}} \) and \( d_{i,j} = \sqrt{(x_{i,j}^{\text{UAV}} - x_{i,j}^{\text{GD}})^2 + (y_{i,j}^{\text{UAV}} - y_{i,j}^{\text{GD}})^2 + h_{i,j}^2} \).

Next, we introduce (2) to (40) and obtain:

\[
10 \log_{10} \left( \frac{4 \pi h_{i,j}}{G \lambda^2} \right)^2 + \left( \eta_{\text{NLoS}} - \eta_{\text{LoS}} \right) - \eta_{\text{NLoS}} \leq L_{i,j}^{\text{D2V}} \tag{41}
\]

where (41) holds, if and only if \( \mathbb{P}_{\text{LoS}} = 1 \), i.e., UAV \( j \) perpendicularly hovers over TDCC \( i \). Further, we need to determine the boundary of \( h_{i,j} \) so as to solve the extremum of (41).

**Proposition 3:** The lower bound and upper bound of \( h_{i,j} \) are given by:

\[
\sqrt{\frac{c_j \left( \ln \left( c_j \left( 4 \pi \right)^2 / G \lambda^2 \right) + 1 \right) G \lambda^2}{4 \pi^2}} \leq h_{i,j} \leq \sqrt{\frac{P_{\text{max}}^{\text{GD}} G \lambda^2}{4 \pi^2} \gamma \left( N_0 + \sum_{k \in S_j} P_{\text{min}} \right)} \tag{42}
\]

where \( C = \frac{\eta_{\text{NLoS}} - \eta_{\text{LoS}}}{1 + a \exp[-b(\pi/2-a)]} - \eta_{\text{NLoS}} \), \( \gamma \) is the threshold of SINR, and \( c_j \) is the terrestrial constraint (4) on UAV \( j \).

**Proof:** See Appendix A.

Given Proposition 3, \( L_{i,j}^{\text{D2V}} \) is minimized in (38), and \( L_{i,j}^{\text{D2V}} \) in (39) is maximized simultaneously, i.e., minimizing \( d_{i,j} \) yields the maximum of \( d_{k,j} \). Thus, we can obtain the waypoint that can minimize the path loss between UAV \( j \) and TDCC \( i \), i.e.,

\[
\begin{align*}
    x_{i,j}^{\text{UAV}} &= x_{i,j}^{\text{GD}}, \\
    y_{i,j}^{\text{UAV}} &= y_{i,j}^{\text{GD}}, \\
    z_{i,j}^{\text{UAV}} &= z_{i,j}^{\text{GD}} + h_{i,j}^*,
\end{align*}
\]

and UAV \( j \)’s final optimal waypoint can be determined by \( \arg \min \left( \left( x_{i,j}^{\text{GD}}, y_{i,j}^{\text{GD}}, z_{i,j}^{\text{GD}} + h_{i,j}^* \right) \right), i \in S_j \).

Consequently, by jointly optimizing the G2A path loss and the GD transmit power, TDCCs can transmit data with the optimal channel capacity. In addition, the heuristic algorithm is proposed to deploy UAVs to fetch data returned from TDCCs, as shown in Algorithm 5, and the computational complexity is \( \max \left\{ \mathcal{O}(M \mid N_1 \mid), \ldots, \mathcal{O}(M \mid N_1 \mid) \right\} \).

**Step1:** Initially, given \( M \) UAVs and the set of TDCCs \( T \), where \( M \leq |T| \), we allocate \( M \) UAVs to \( M \) TDCCs randomly and generate the set of remaining TDCCs, denoted by \( \{1, \ldots, |T| - M\} \).

**Step2:** Once UAV \( j \) finishes its current mission, it will be dispatched to TDCC \( i \) by
minimizing \( d_{i,j} \), where \( i \in \{1,\ldots,|T| - M\} \), and we remove \( i \) from \( \{1,\ldots,|T| - M\} \).

**Step3:** Repeat **Step2** until \( \{1,\ldots,|T| - M\} \) is empty to guarantee that each TDCC’s data is received.

**Algorithm 5** Algorithm for Waypoint Updating

1: **Input:** Set of TDCCs \( T \), Set of DEM \( D \), and Number of UAVs \( M \)
2: **Output:** UAV position matrix \( U \)
3: **Initialize:** Number of iteration \( M \), position matrix \( U_{M \times |T|} \), and null matrix \( N_{M \times |T|} \)
4: **Allocate** \( M \) UAVs to \( M \) TDCCs randomly, remove the indexes of \( M \) TDCCs from \( T \) to obtain the index set \( \{1,2,\ldots,|T| - M\} \), and add the corresponding index of TDCC to \( N \)
5: while \( \{1,2,\ldots,|T| - M\} \neq \emptyset \) do
6: Allocate \( T_j,i \in \{1,2,\ldots,|T| - M\} \) to UAV \( j \) by minimize \( d_{i,j} \), remove \( i \) from \( \{1,2,\ldots,|T| - M\} \), and add \( T_j \) to \( N_j \)
7: end while
8: for \( j = 1,2,\ldots,M \) do
9: for \( k = 1,2,\ldots,|N| \) do
10: Let \( x_{i,j}^{UAV} = x_{k}^{GD} \) and \( y_{j}^{UAV} = y_{k}^{GD} \)
11: Compute the boundary of \( h_{k,j} \) based on (42)
12: Update \( z_{j}^{UAV} = h_{k,j} + z_{k}^{GD} \) by minimizing \( h_{k,j} \) and add \( \{x_{j}^{UAV},y_{j}^{UAV},z_{j}^{UAV}\} \) to \( U_{j} \)
13: end for
14: end for
15: return \( U \)

Given any two waypoints derived from UAV waypoint planning, we need to optimize \( T_M \) for each UAV. To effectively save the flight time, the control model of quadrotors is defined as follows [40]:

\[
\begin{align*}
\dot{x}(t) & = \frac{f}{m} \left( \sin(\psi) \sin(\phi) + \cos(\psi) \sin(\theta) \cos(\phi) \right) + \frac{(f \cdot R)_x}{m} \\
\dot{y}(t) & = \frac{f}{m} \left( -\cos(\psi) \sin(\phi) + \cos(\psi) \sin(\theta) \sin(\phi) \right) + \frac{(f \cdot R)_y}{m} \\
\dot{z}(t) & = \frac{f}{m} \cos(\theta) \cos(\phi) - g + \frac{(f \cdot R)_z}{m} \\
\dot{\phi}(t) & = \frac{\tau_x}{I_{xx}} \\
\dot{\theta}(t) & = \frac{\tau_y}{I_{yy}} \\
\dot{\psi}(t) & = \frac{\tau_z}{I_{zz}}
\end{align*}
\]

(43)

where \( \phi \) is the roll, \( \theta \) is the pitch, \( \psi \) is the yaw, \( f \) is the lift, \( f \) is the wind-speed vector, and \( \tau = [\tau_x, \tau_y, \tau_z] \) is the torque that meets:
where $c_T$ is the thrust coefficient, $c_M$ is the torque coefficient, $d_r$ is the fuselage radius and $\sigma$ is the motor speed.

Based on optimal control [16], we define the optimization problem of $T_M$ as follows:

$$\text{(P2-b):} \quad \min T_M = t$$

subject to

$$\dot{\mathbf{p}}(t) = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \mathbf{p}(t) + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \alpha(t)$$

where $\mathbf{p}(t) = [x_j^\text{UAV}(t), y_j^\text{UAV}(t), z_j^\text{UAV}(t)]^T$, $\alpha(t) = \begin{cases} a_{\text{max}}, & 0 \leq t \leq \tilde{t} \\ a_{\text{min}}, & \tilde{t} \leq t \leq t^* \end{cases}$ is the control, and $t^*$ and $\tilde{t}$ are the optimal flight time and the switching time, respectively.

Proposition 4: $t^*$ and $\tilde{t}$ are given by:

$$t^* = \frac{4d(t^*)g \cos(\theta)}{a_{\text{max}}^2 + a_{\text{max}}^2 g \cos(\theta)}$$

$$\tilde{t} = t^* a_{\text{max}} + 1$$

where $d(t^*)$ is the displacement, $\theta$ is the pitch, and $a_{\text{max}}$ is the maximum acceleration.

Proof: See Appendix B.

To generate a final UAV trajectory, four Proportional-Integral-Differential-based (PID) controllers are used to generate desired commands [41].

First, the location controller is given by:

$$\mathbf{F} = g^{-1} A^{-1} \left( K_p e_v + K_i \int e_v + K_o \dot{e}_v - a \right)$$

$$f = m \left( g + K_p e_v + K_i \int e_v + K_o \dot{e}_v - \frac{\mathbf{F}}{m} \right)$$

where $\mathbf{F} = [F_x, F_y, F_z]^T$, $a = \begin{bmatrix} F_x/m, F_y/m \end{bmatrix}^T$, $A^{-1} = \begin{bmatrix} \cos(\psi) & -\sin(\psi) \\ \sin(\psi) & \cos(\psi) \end{bmatrix}^{-1}$, $\mathbf{F} = \mathbf{f} \cdot \mathbf{R}$, $K_p$, $K_i$, and $K_o$ are PID coefficients, and $e$ is the system error.

Second, the torque controller can be expressed as follows:

$$\tau = K_p e_\omega + K_i \int e_\omega + K_o \dot{e}_\omega$$
where \( \tau = [\tau_x, \tau_y, \tau_z]^T \) is the torque.

Next, based on (47)-(47), we can obtain the desired speeds of four motors:

\[
\begin{bmatrix}
\bar{\omega}_1^2 \\
\bar{\omega}_2^2 \\
\bar{\omega}_3^2 \\
\bar{\omega}_4^2 \\
\end{bmatrix} =
\begin{bmatrix}
c_T & c_T & c_T & c_T \\
0 & -d,c_T & 0 & d,c_T \\
d,c_T & 0 & -d,c_T & 0 \\
c_M & -c_M & c_M & -c_M \\
\end{bmatrix}^{-1}
\begin{bmatrix}
f \\
\tau \\
\end{bmatrix}
\tag{49}
\]

Finally, the desired command is obtained:

\[
\kappa = K_p \bar{\omega} + K_i \int \bar{\omega} + K_d \dot{\bar{\omega}}
\tag{50}
\]

Given (50), we can obtain the final UAV trajectory.

2) Optimal Solution of P2

Generally, a MOP can be defined as follows [42]:

\[
\begin{align*}
\max & \quad F(x) = (f_1(x), \ldots, f_m(x)) \\
\text{s.t.} & \quad x \in \Omega
\end{align*}
\tag{51}
\]

where \( \Omega \) is the variable space. As illustrated in [42], we can know that no variable in \( \Omega \) can maximize all objective functions in (51) simultaneously, because the constraints on (51) contradict with each other. Therefore, the best tradeoff should be selected by searching the PF [43].

Based on (P2-a) and (P2-b), we need to solve the optimal number of UAVs and the optimal transmit power of TDCCs by jointly minimizing the time for emergency response and the energy consumption. Since UAVs work simultaneously, \( \sum_{j=M}^{T_j} \) is actually a minimization-maximization problem (MMP), i.e., minimize the maximum of response time, but \( \sum_{j=M}^E_j \) is a minimization problem, i.e., minimize the cumulative energy consumption:

\[
\begin{align*}
\min & \quad \max \{T_i, \ldots, T_j\}, j \in \mathcal{M} \\
\min & \quad \sum_{j=\mathcal{M}} E_j
\end{align*}
\tag{52}
\tag{53}
\]

Further, we redefine (P2) as the following MOP:
\[
\begin{align*}
\min f_1(x_1, x_2) &= \max \left\{ T_j(x_1, x_2), \ldots, T_j(x_1, x_2) \right\}, \quad j \in \mathcal{M} \\
\min f_2(x_1, x_2) &= \sum_{j \in \mathcal{M}} E_j(x_1, x_2) \\
\text{s.t.} \quad g_1(x_1, x_2) &= x_2 - P_{\min}^{\text{TDCC}} \geq 0, \\
&= E_{\max} - E_j(x_1, x_2) \geq 0, \\
1 &\leq x_1 \leq |\mathcal{T}|, \\
0 &\leq x_2 \leq P_{\max}^{\text{TDCC}} 
\end{align*}
\]

where \( x_i \) represents the number of UAVs, \( x_2 \) represents the TDCC transmit power, \( \mathcal{T} \) is the set of TDCCs, whose entry is the subset of TDCCs served by UAV \( j \), and \( 1 \leq x_1 \leq |\mathcal{T}| \) means that we need at least one UAV and at most \( |\mathcal{T}| \) UAVs. Following (54), the Tchebycheff Method (TM) is adopted to simplified (54) as follows:

\[
\begin{align*}
\min g_{\text{TM}}(x_1, x_2 | \lambda, z^*) &= \max \left\{ \lambda \left| f_i(x_1, x_2) - z_i^* \right| \right\} \\
\text{s.t.} \quad 1 &\leq x_1 \leq |\mathcal{T}|, \\
P_{\min}^{\text{TDCC}} \leq x_2 \leq P_{\max}^{\text{TDCC}}, \\
0 &\leq E_{\max} - E_j(x_1, x_2) 
\end{align*}
\]

where \( z^* = (z_1^*, z_2^*) \) is the reference vector, and \( \lambda = (\lambda_1, \lambda_2) \) is the weight vector. Thus, our target is to minimize the interval between different \( g_{\text{TM}}(x_1, x_2 | \lambda, z^*) \), and the TM generates the follows during each searching process:

\[
\begin{align*}
\{x_1, \ldots, x_i\} \\
F(x_i) \\
z_i^* \\
\{F(x_i)\}
\end{align*}
\]

where \( x_i \) is the current solution to objective function \( i \), \( F(x_i) \) is the function value of (55), \( z_i^* \) is the best value of objective function \( i \), and \( \{F(x_i)\} \) is the external population for non-dominated solutions. Based on \( \{F(x_i)\} \), we need to search the optimal solution from the PF. Here, the KN-based method is adopted to determine the Pareto Optimality (PO), and the solution of PO is given by [44]:

\[
\min \sum_{i \in \mathcal{F}, j \neq i} \max \left[ 0, \frac{F(x_i) - F(x_j)}{\sum_{i \in \mathcal{F}, j \neq i} \max \left[ 0, F(x_i) - F(x_j) \right]} \right]
\]

\[
\sum_{i \in \mathcal{F}, j \neq i} \max \left[ 0, F(x_i) - F(x_j) \right]
\]
IV. SIMULATION RESULTS AND DISCUSSIONS

In our simulations, we randomly generate a $G = (V, L, W)$ over a $3 \times 3$ km geographic area, where the distribution radius $r$ is 1 km, and the size of $G$ is 50. Considering the multiple constraints on the system, Table I and Table II list the simulation parameters for D2D and D2V networks, respectively, Table III lists the simulation parameters for motion planning. To verify the effectiveness of the proposed system, we compare our system with the work in [23] that did not take into account D2D communication. In [23], the UAV-aided D2V network was proposed to collect GD emergency data, where UAVs worked as dynamic aerial BSs (DABS) to fetch data from each GD, but the workload of UAVs and the system resources were not managed effectively. In contrast, we first divide the D2D network and determine the locations of TDCCs, from which the UAVs are deployed to receive data. Next, the MOP-based D2V network is proposed by solving the optimal number of UAVs and the optimal transmit power of TDCCs. In addition, all simulation results are averaged over a number of independent experiments through Python, like NUMPY, CVXPY, PYMOO, NETWORKX, etc.

| Table I | SIMULATION PARAMETERS FOR D2D NETWORK MODEL |
| --- | --- | --- |
| Parameter | Description | Value |
| $a$ | Carrier frequency constant | 11.95 |
| $b$ | Environment constant | 0.14 |
| $\eta_{\text{LoS}}$ | Additional path loss for LoS | 3 dB |
| $\eta_{\text{NLoS}}$ | Additional path loss for NLoS | 23 dB |
| $\mu$ | Packet size | 124 byte |
| $G$ | Gain | 1 |
| $N_0$ | Noise power | $-130$ dBm |
| $\sigma^2$ | Standard deviation of path loss | 3.65 dB |
| $\epsilon$ | Threshold of outage probability | 0.01 |
| $P_{\text{min}}$ | Threshold of received power | 5 dB |
| $P_{\text{max}}$ | Maximum transmit power for GDs | 10 mW |

| Table II | SIMULATION PARAMETERS FOR D2V NETWORK MODEL |
| --- | --- | --- |
| Parameter | Description | Value |
| $m$ | Mass | 4 kg |
| $g$ | Gravity acceleration | $9.8 \text{ m/s}^2$ |
| $\rho$ | Air density | $1.225 \text{ kg/m}^3$ |
| $c_d$ | Drag coefficient | $0.117 \text{ N/(m/s)}^2$ |
| $c_b$ | Blade chord | 0.1 m |
| $N_b$ | Number of blades | 4 |
| $d_r$ | Fuselage radius | 0.3 m |
| $\delta$ | Buffer radius | 20.3 m |
### Simulation Parameters for Motion Planning

| Parameter | Description                  | Value            |
|-----------|------------------------------|------------------|
| $I_{xx}$  | $x$-axis inertia moment      | $6.302 \times 10^{-2}$ kg m$^2$ |  
| $I_{yy}$  | $y$-axis inertia moment      | $6.302 \times 10^{-2}$ kg m$^2$ |  
| $I_{zz}$  | $z$-axis inertia moment      | $1.171 \times 10^{-2}$ kg m$^2$ |  
| $f_{\text{max}}$ | Maximum lift              | $68.1$ N       |  
| $c_T$    | Thrust coefficient          | $2.646 \times 10^{-5}$ N/(rad/s)$^2$ |  
| $c_M$    | Torque coefficient          | $4.411 \times 10^{-7}$ N m/(rad/s)$^2$ |  

In Fig. 3, we present the result of ONP of the D2D network derived from Algorithm 4. Fig. 3(a) illustrates the convergence of modularity $Q$ of the D2D network, i.e., by iterating the two steps: 1) optimizing community division in (15) and 2) optimizing wireless transmission performance in (24), the ONP can be determined, and the maximum modularity $Q$ converges to 1.34 at the 10th update. From Fig. 3(b), we can see that the initial D2D network can be finally divided into 8 communities, where each community member (ordinary node) will transmit collected emergency information toward its TDCC (key node). Clearly, if a GD is located in the remote area or blocked by terrains, it will be also identified as a community with just one community member. Thus, with the support of UAVs, the isolated nodes’ data will be fetched back, thus effectively enhancing the ECN coverage.

![Convergence of modularity $Q$.](image1.png)  
![D2D network communities.](image2.png)

Fig. 3. Optimal Network Partition.

Fig. 4 shows the distribution of TDCCs derived from (P1). As illustrated in Fig. 4, the TDCC can be found out in each community. Thus, the community members just need to transmit their data toward their corresponding TDCCs, and UAVs are only dispatched to fetch data from the TDCCs without communicating with all GDs, which effectively saves the energy consumed by wireless communication and motion, and also shortens the amount of time for emergency response. Moreover, besides the weighted-directed-graph (WDG)-based network model in this article, according to (28)-(33), we can see that our proposed method can be also applied to other network models to determine the importance of network nodes, such as a directed graph (DG).
or a weighted graph (WG). For instance, a DG model can be used to discover relay nodes in wireless sensor networks (WSN) [45].

Fig. 4. Optimal solution of P1.

Fig. 5 shows the results of UAV waypoint planning, by which the UAV leaves the take-off point (e.g., the rescue center) and updates its three-dimension (3D) position derived from Algorithm 5 to minimize the G2A path loss between the UAV and TDCCs. The path gain improves by 9.0 dB, as shown in Fig. 5(a), and a UAV finally hovers at the optimal position to optimize the wireless transmission performance in the uplink. Next, from Fig. 5(b), we can find that the optimized G2A channel capacity converges from 4.7 kbps to 8.2 kbps, thus improving by 3.5 kbps, i.e., given the fixed-length of data packet, the capacity theoretically saves nearly half of transmission time. Therefore, the proposed algorithm enhances the uplink capacity and further improve the efficiency of collecting data returned from TDCCs. From (37), we can find that increasing bandwidth can also improve the channel capacity.

Fig. 5. UAV waypoint planning.

Fig. 6 presents the results of UAV motion planning by optimal control. UAVs need to hover over TDCCs until they receive data returned from TDCCs completely, so the initial and final velocities between adjacent waypoints equal 0 m/s. To remarkably improve the efficiency of emergency response, UAVs dynamically update their aerial attitudes by maximizing the acceleration along their moving directions, subject to a set of environment and energy constraints. Therefore, as shown in Fig. 6(a), the optimal control-based UAV can save 61% of moving time compared with the one without
control (uniform velocity). Moreover, from Fig. 6(b) and (11), we can know that the UAV energy is mainly consumed by motion, i.e., the motion energy consumption is the main factor used to determine the number of waypoints and the wireless coverage.

![Fig. 6. UAV motion planning.](image)

In Fig. 7, we present the potential solutions of (P2) by solving the number of UAVs and the transmit power of TDCCs simultaneously, i.e., minimize the amount of time for emergency response and the UAV energy consumed by receiving data and aerial motion. From Fig. 7(a), the PF of (55) that consists of some sparse sub-optimal points is obtained by MOEA/D, where the reference vector $z^*$ is uniformly generated by the Das-Dennis method [44]. Then, according to the sparsity and the convergence of the PF, we further determine the PO by the tradeoff metric in (57), and the best tradeoff point is selected as the PO, as shown in Fig. 7(b). Based on the PO, the optimal solution of (55) is determined.

![Fig. 7. Energy-efficient solutions.](image)

Fig. 8 shows the optimal solution of the proposed ECN by fusing D2D and D2V networks. From Fig. 8(a), we can see that the optimal number of UAVs derived from MOEA/D equals 4, i.e., 4 UAVs are simultaneously dispatched to perform emergency missions. Here, the amount of time for emergency response and the total energy consumption both depend on wireless transmission and aerial motion. Since (52) is a MMP, as shown in Fig. 8(a), the optimal emergency response time depends on the maximum time, namely, the amount of time spent by UAV 4, and our proposed ECN saves 47% of the amount of time for emergency response, thus improving response
efficiency remarkably. However, (53) is just a minimization problem, so its optimal solution depends on the sum of energy consumed by 4 UAVs, and the total energy consumption is 238 kJ, as shown in Fig. 8(b). Moreover, as shown in Fig. 8(c), the energy efficiency is expressed as the total energy consumption divided by response time, and the optimal balance is achieved when the solution with the minimum value is obtained.

Fig. 8. Optimal solution of P2.

V. CONCLUSION

With a focus on the energy-efficient emergency response, this article proposed a hybrid D2D and D2V network to collect and transmit emergency data. Specifically, we first established the D2D network from the perspective of complex networks, including network partition and key node detection. The D2D network was divided into small network communities, and the TDCC in each community was found out to receive and cache data returned from community members, which could extend the coverage of the D2D network and compensate the energy limitation of UAVs. Next, based on the locations of TDCCs, the D2V network was established. We updated the positions of UAVs to enhance the G2A channel capacity and dispatched each UAV to fetch data by optimal control, which effectively saved the amount of time for collecting data and aerial moving. Finally, the optimal energy efficiency was obtained by simultaneously minimizing the time and the energy for emergency response. The simulation results demonstrated that the hybrid D2D and D2V network saved 47% emergency response time compared with previous works. Thus, the proposed ECN could make contributions to post-disaster emergency response.

However, there are other potential problems not addressed in this article, some of which are worthy of being discussed in future works. It is necessary to introduce other types of communication channels to deal with different emergency scenarios (e.g., large-scale IoT and underwater IoT (UIoT)), such as quantum communication, optical or acoustic communication, etc. For large-scale IoT, ECNs should be capable of
all-weather monitoring, so satellites can work as relay-nodes to assist back-haul communication. For UIoT, according to the distance between different underwater devices, the performance of communication links varies with time, so the optimal communication link can be determined by optimizing delivery or overhead ratio. Moreover, how to establish an integrated space-air-ground-sea (SAGS) ECN is still a great challenge, and it remains unclear how to efficiently and jointly schedule different unmanned vehicles.

APPENDIX

A. Proof of Proposition 3

Following (41), we first obtain the inequality of SINR by $h_{i,j} = d_{i,j}$:

$$
\gamma \leq \text{SINR} = \frac{P_{i,j}}{10^{\frac{C_{i,j}}{10}} \left( N_0 + \sum_{k \in S_{j\cup}} P_{k,j} \right) / 10^{\frac{C_{i,j}}{10}}} \left( N_0 + \sum_{k \in S_{j\cup}} P_{k,j} \right)
$$

(58)

Then, we introduce (41) into (58) and obtain:

$$
\left( \frac{4\pi h_{i,j}}{G\lambda^2} \right)^2 \leq \frac{P_{i,j}10^{(C_{i,j}/10)}}{\gamma \left( N_0 + \sum_{k \in S_{j\cup}} P_{k,j} / 10^{(C_{i,j}/10)} \right)} \leq \frac{P_{\text{GD}}^{10^{(C_{i,j}/10)}}}{\gamma \left( N_0 + \sum_{k \in S_{j\cup}} P_{\text{min}} \right)}
$$

(59)

where $C$ is a constant in (41). Following (59), the upper bound of $h_{i,j}$ is obtained:

$$
h_{i,j} \leq \sqrt{\frac{P_{\text{GD}}G\lambda^210^{(C_{i,j}/10)}}{(4\pi)^2 \gamma \left( N_0 + \sum_{k \in S_{j\cup}} P_{\text{min}} \right)}}
$$

(60)

Next, we rewrite (41) and obtain:

$$
10 \log_{10} \left( \frac{4\pi h_{i,j}}{G\lambda^2} \right)^2 = 10 \log_{10} \left( \frac{4\pi h_{i,j}}{G\lambda^2} \right)^2 = \ln \left( c_j \left( \frac{4\pi h_{i,j}}{c_j G\lambda^2} \right)^2 -1 + 1 \right) = \ln \left( c_j \right) + \sum_{n=1}^{\infty} (-1)^{n-1} \frac{(4\pi h_{i,j})^2}{c_j G\lambda^2} \right)^n
$$

(61)

where $c_j$ is the constraint of (4). Given (61), we closely approximate the lower bound of $h_{i,j}$ by Taylor’s formula [46]:
\[
\ln(c_j) + \sum_{n=1}^{\infty} \frac{(-1)^{n-1}}{n} \left( \frac{(4\pi h_{i,j})^2}{c_j G \lambda^2} - 1 \right)^n = \ln(c_j) + \left( \frac{(4\pi h_{i,j})^2}{c_j G \lambda^2} - 1 \right),
\]
\[
\ln(c_j) + \left( \frac{(4\pi h_{i,j})^2}{c_j G \lambda^2} - 1 \right) = \ln \left( \frac{(4\pi h_{i,j})^2}{G \lambda^2} \right) \geq \ln \left( \frac{(4\pi c_j)^2}{G \lambda^2} \right),
\]
\[
\sqrt{c_j \left( \ln \left( \frac{(4\pi c_j)^2}{G \lambda^2} \right) + 1 \right) G \lambda^2} \leq h_{i,j}
\]

Finally, (60) and (62) prove the proposition.

**B. Proof of Proposition 4**

First, we express the velocity constraint as follows:
\[
a_{max} \tilde{t} + a_{min}(t^* - \tilde{t}) = 0
\]

Then, we can obtain the expression of \(\tilde{t}\):
\[
\tilde{t} = \frac{-t^* a_{min}}{a_{max} - a_{min}}
\]

Next, given \((x_A^{UAV}, y_A^{UAV}, z_A^{UAV})\) and \((x_B^{UAV}, y_B^{UAV}, z_B^{UAV})\), we need to guarantee that the resultant force is in the same direction as \(\overline{AB}\), and can obtain:
\[
p = \arcsin \left( \frac{\|F\| \sin (q) + mg \sin (\theta)}{f_{max}} \right)
\]

where \(p\) is the angle between between \(\overline{AB}\) and \(f_{max}\), \(q = \arccos \left( \frac{\|F\| \cdot \|\overline{AB}\|}{\|F\| \cdot \|\overline{AB}\|} \right)\), \(f_{max}\) is the maximum lift, and \(\theta\) and \(\psi\) satisfy:
\[
\left\{ \begin{array}{l}
F \cos (\theta)_{AB} = \|F\| \cos (\theta)_{W} + f_{max} \cos (\theta) \\
\|F\| \sin (\theta)_{W} \sin (\psi)_{AB} - \psi_{W} = f_{max} \sin (\theta) \sin (\psi - \psi_{AB})
\end{array} \right.
\]

where \(\theta_{AB} = \arccos \left( \frac{z_B^{UAV} - z_A^{UAV}}{d(t^*)} \right)\), \(\psi_{AB} = \arctan \left( \frac{y_B^{UAV} - y_A^{UAV}}{x_B^{UAV} - x_A^{UAV}} \right)\), \(\theta_{W} = \arccos \left( \frac{\|F\|}{\|F\|} \right)\), \(\psi_{W} = \arctan \left( \frac{F_y}{F_x} \right)\), and \(F = \sqrt{f_{max}^2 + \|F\|^2 + 2f_{max} \|F\| \cos (p + q) - mg \cos (\theta)}\).

By projecting \(f_{max}\) and \(F\) on \(\overline{AB}\), the expressions of \(a_{max}\) and \(a_{min}\) are given by:
\[
\left\{ \begin{array}{l}
a_{max} = f_{max} \cdot \sin (\theta) + \|F\| \cos (q) - mg \cos (\theta) \\
a_{min} = a_{max} + 2g \cos (\theta)
\end{array} \right.
\]

Finally, following (63)-(67), \(t^*\) can be solved:
\[ d(t^*) = \frac{1}{2} a_{\max}^2 + a_{\max} \bar{t} (t^* - \bar{t}) + \frac{1}{2} a_{\min} (t^* - \bar{t})^2, \]
\[ d(t^*) = \frac{1}{2} a_{\max} \left( \frac{-t^* a_{\min}}{a_{\max} - a_{\min}} \right)^2 + a_{\max} \left( \frac{-t^* a_{\min}}{a_{\max} - a_{\min}} \right) \left( t^* - \frac{-t^* a_{\min}}{a_{\max} - a_{\min}} \right) + \frac{1}{2} a_{\min} \left( t^* - \frac{-t^* a_{\min}}{a_{\max} - a_{\min}} \right)^2, \]
\[ 2d(t^*) = a_{\max} \left( \frac{t^* (a_{\max} + 2g \cos(\theta))}{2g \cos(\theta)} \right)^2 + a_{\max} \left( \frac{-t^* (a_{\max} + 2g \cos(\theta))}{g \cos(\theta)} \right) \left( t^* a_{\max} \right) \]
\[ + (a_{\max} + 2g \cos(\theta)) \left( \frac{-t^* a_{\max}}{2g \cos(\theta)} \right)^2 \]
\[ = a_{\max} \left( t^* (a_{\max} + 2g \cos(\theta)) \right)^2 - 2a_{\max}^{2} t^* \left( a_{\max} + 2g \cos(\theta) \right) + a_{\max}^{2} t^* \left( a_{\max} + 2g \cos(\theta) \right) \]
\[ = 4g^2 \cos(\theta)^2, \]
\[ t^* = \sqrt{\frac{4d(t^*) g \cos(\theta)}{a_{\max}^2 + 2a_{\max} g \cos(\theta)}}. \]  

Clearly, (64) and (68) prove the proposition.

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