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RESEARCH ARTICLE

# Lyapunov Optimization-Based Online Positioning in UAV-Assisted Emergency Communications

**JUNGHWA KANG[1], (Student Member, IEEE), KYEONGROK KIM[2], (Member, IEEE), HOWON LEE[3], (Senior Member, IEEE), AND JAE-HYUN KIM[4], (Member, IEEE)**

[1]Land Combat System Center, Hanwha Systems, Sungnam 13552, South Korea
[2]Satellite System 1 Team, Hanwha Systems, Yongin 17121, South Korea
[3]School of Electronic and Electrical Engineering and IITC, Hankyong National University, Anseong 17579, South Korea
[4]Department of Electrical and Computer Engineering, Ajou University, Suwon 16499, South Korea

Corresponding authors: Jae-Hyun Kim (jkim@ajou.ac.kr) and Howon Lee (hwlee@hknu.ac.kr)

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**ABSTRACT** In disasters, unmanned aerial vehicles (UAVs) can be used as aerial base stations (BSs) when terrestrial BSs are unavailable. Although most studies have focused on optimal UAV localization to provide efficient network connectivity for outdoor users, supporting indoor users is also of great importance. Additionally, fairly providing network connectivity to as many indoor users as possible is critical in emergencies. Therefore, we propose a table-based fair transmission algorithm based on carrier-sense multiple access with collision avoidance (CSMA/CA) that aims to provide as many equal opportunities as possible. Moreover, we propose a Lyapunov optimization-based optimal UAV positioning algorithm to satisfy various disaster requirements. To analyze the proposed algorithm's performance, two building types were considered: standard- and factory-type buildings. We then compared the proposed table-based fair transmission algorithm with the conventional protocol according to various building types. Furthermore, via intensive simulations, we demonstrated the Lyapunov optimization-derived UAV movements according to situational requirement variations.

**INDEX TERMS** Unmanned aerial vehicle, online UAV positioning, indoor-to-outdoor path loss model, Lyapunov optimization, UAV-assisted emergency communications.

## I. INTRODUCTION

Due to the physical and economic difficulties of installing existing terrestrial base stations (BSs), in addition to the radio signal propagation range's limitations, communication becomes increasingly difficult in specific areas, such as mountains, deserts, and oceans. Recently, various studies have been conducted on covering shadow areas via moving BSs using unmanned aerial vehicles (UAVs) or low Earth orbit (LEO) satellites [1]. Specifically, wireless communications using UAVs have been of interest to military and civilian users due to their low cost and high utility [2], [3].

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Additionally, studies related to aerial base stations using UAVs are being actively conducted due to their operational convenience in local areas, such as cities or mountainous, where communication is unavailable.

However, UAV communications are still critically disadvantaged by the limited battery compared to terrestrial BSs. Thus, this severely limits the UAV network operation time. To overcome these limitations, we should consider researching UAV movement optimization. To overcome these limitations, we should consider researching UAV movement optimization. [4], [5], [6], [7]. Energy-efficient UAV path planning was proposed for disaster scenarios in [4]. Moreover, the authors in [5] proposed a Q-Learning-based power allocation method for sum capacity maximization. In [6], the authors proposed a UAV path for throughput maximization using particle swarm optimization. The authors in [7] proposed the optimal UAV movements for wireless service efficiency in emergency communications. Even though these studies only considered the UAV movements that support outdoor users, there has been a great demand for wireless network connectivity in indoor environments. Hence, the role of UAVs in indoor disaster environments is even more important due to the unavailability of wireless network connectivity sprouting from environmental problems. When considering indoor users in disaster environments, an additional path loss due to multiple floors and walls in buildings exists. Therefore, effective UAV movements are essential for providing seamless connectivity. However, recent studies that consider UAV communications for indoor users have found the UAV's 3D optimal location without finding their optimal path [8], [9]. Furthermore, these studies focused on the optimization of their transmission power or coverage. This implies that existing studies still have not managed to fairly provide adequate wireless connectivity to as many indoor users as possible during disasters.

Moreover, the authors in [10] used an ITU-R path loss model that considered the building penetration loss to serve indoor users. This model does not consider the path loss through the floor because the signal propagating through the building's window is large. However, actual windowless factory buildings have a greater signal attenuation than standard ones because the path loss through the floor must be considered as well. In this paper, we evaluate the problem using both two path loss models by deriving the floor penetration loss using the ITU-R path loss model [11].

To address the issues in existing studies, we propose a table-based fair transmission algorithm that serves as many indoor users as possible at least once. Additionally, we propose optimal UAV placement in terms of system throughput, which makes supporting users with various kinds of service requirements on different floors and rooms possible. Accordingly, we consider both floor and wall path losses in indoor environments for emergency communications. Consequently, we adopt the Lyapunov optimization to formulate our proposed algorithm and find the optimal solution. Our contributions are summarized as follows:

- **Table-based fair transmission:** we proposed the table-based fair transmission algorithm to improve the conventional CSMA protocol's performance. In the proposed algorithm, and for the sake of fairness, the UAV and each user share a table that has transmission information. When a user transmits data once, it transmits it to the UAV with a value of 1 in a frame. The UAV then fills the corresponding user index in the table with 1. A user that has transmitted once does not participate in the channel competition. When all columns in the UAV become filled with the values of 1, all users start contention anew. Consequently, the proposed fair transmission algorithm can improve indoor user fairness in emergency communications.

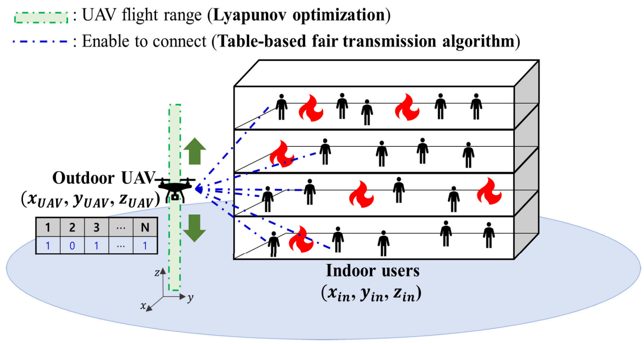


**FIGURE 1.** The proposed system model with the 3D coordination for UAV-assisted emergency communications.

- **Lyapunov optimization-based optimal UAV positioning:** we proposed an optimal UAV positioning algorithm using the Lyapunov optimization technique, satisfying various scenario requirements. When user data transmission is fairly guaranteed through the data transmission algorithm, the optimal placement of the UAV is determined based on the placement goal. Examples of the latter could be the system throughput and supported user diversity in the building, providing seamless network connectivity in emergency communications.
- **Performance analysis considering two building types:** we analyzed the proposed algorithm's performance by considering two building types: standard- and factory-type buildings. The latter are windowless. Thus, we should simultaneously consider the floor and wall losses. This implies that the factory-type building may face more critical situations in case of disasters.

The rests of this paper is divided as follows. Sec. II describes the system model and the mathematical analysis. In Sec. III, we propose the optimal UAV positioning algorithm using Lyapunov optimization. In Sec. IV, we analyze the results according to the disaster scenario and compare it with other conventional algorithms. Finally, we conclude this paper in Sec. V.

## II. SYSTEM MODEL

In our system model, we assume that there is one UAV outside a building and many indoor users on the inside. The three-dimensional (3D) coordination of the UAV and indoor users is illustrated in Fig. 1. In case of disasters, indoor users cannot be provided with seamless network connectivity. Therefore, UAV-assisted indoor communication is required to rescue and immediately connect with indoor users. In this paper, we assume that the UAV knows the users' locations inside the building.

### A. INDOOR-TO-OUTDOOR PATH LOSS MODEL BY ITU-R [11]

The indoor-to-outdoor path loss model was presented by ITU-R, as shown in Fig. 2(a) [11]. This path loss model is given as

$$PL = PL_b + PL_{wall} + PL_{in}, \tag{1}$$
$$PL_b = 20\log_{10}(f_{GHz}(d)) + 32.4, \tag{2}$$
$$PL_{wall} = g_1 + g_2(1-\cos(\theta))^2, \tag{3}$$
$$PL_{in} = g_3 d_{in}, \tag{4}$$

where $PL$ is the indoor-to-outdoor path loss, $PL_b$ is the basic path loss, $PL_{wall}$ is the building wall's penetration loss, and $PL_{in}$ is the indoor path loss. Also, $d$ is the distance between the UAV and the indoor user, and $d_{in}$ is the distance between the indoor user and the window on the floor where the user is located. $g_1$ and $g_2$ are coefficients (e.g. 14 and 15 in [11]) depending on the building wall's materials, respectively. Moreover, $g_3$ is an in-building constant (e.g. 0.5 in [11]) and $\theta$ is the angle of incidence on the wall.

### B. INDOOR-TO-OUTDOOR PATH LOSS MODEL CONSIDERING THE FLOOR PENETRATION

The path loss model proposed by ITU-R does not consider floor penetration because the signal transmitted through the window is dominant. However, in the case of a factory-type building where the wall loss is more severe than the window, we should consider the floor path loss in addition to the conventional ITU-R path loss model's path loss. This model could be illustrated in Fig. 2(b) and is expressed as:

$$PL = PL_b + PL_{wall} + PL_{in} + PL_{floor}, \tag{5}$$
$$PL_b = 20\log_{10}(f_{GHz}(d_{out} + d_{in}^{floor})) + 32.4, \tag{6}$$
$$PL_{wall} = g_1 + g_2(1-\cos(\theta))^2, \tag{7}$$
$$PL_{floor} = n(g_1 + g_2(1-\sin(\theta))^2), \tag{8}$$
$$PL_{in} = g_3 d_{in}^{floor}, \tag{9}$$

where $d_{out}$ is the distance between the UAV and the point where the building wall meets the propagation path and $d_{in}^{floor}$ is the distance of the indoor path. The floor penetration's angle of incidence is (90° - $\theta$), and the number of floors is $n$.

### C. SINR AND THROUGHPUT CALCULATION

We assess data transmission success using the signal-to-interference-plus-noise ratio (SINR) using the path loss, which is calculated as:

$$SINR = P_{Node} + G_{UAV} + G_{Node} - PL - I - N, \tag{10}$$

where $P_{Node}$ is the user signal's power. $G_{UAV}$ and $G_{Node}$ are the antenna gain values of the UAV and the nodes. $I$ and $N$ are the interference power of other signals and the noise term. If the SINR exceeds the threshold value, the transmission is successful. Therefore, we calculated the throughput as follows:

$$S = \frac{N_{Success} \times T_{Success}}{T_{Total}}, \tag{11}$$

where $S$ is the total throughput and $N_{Success}$ is the number of successful data transmissions. The time required for a

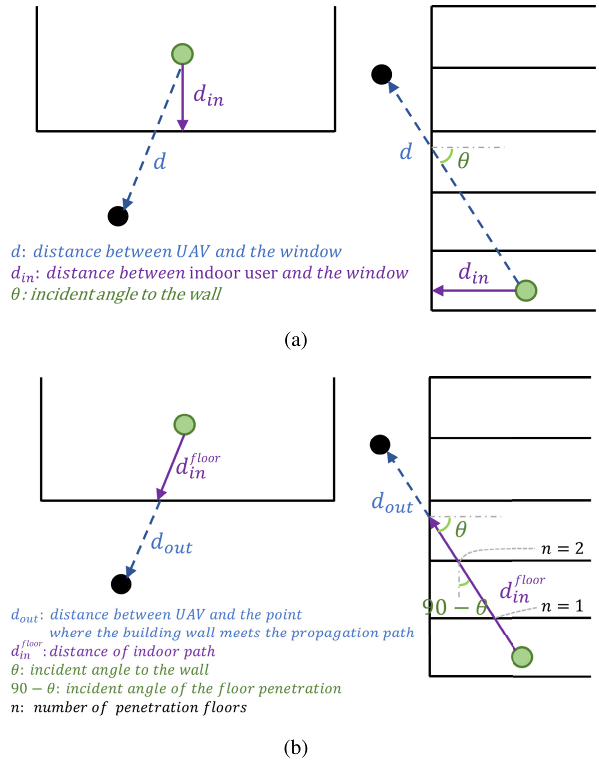


**FIGURE 2.** Indoor-to-outdoor path loss models, (a) When floor penetration is not considered [11], (b) When floor penetration is considered.

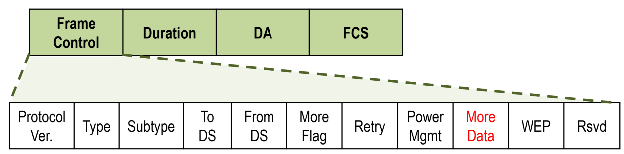


**FIGURE 3.** The acknowledgement (ACK) frame structure.

successful transmission is denoted as $T_{Success}$. $T_{Total}$ is the total transmission time.

## III. THE PROPOSED UAV POSITIONING ALGORITHM WITH FAIR TRANSMISSION

In indoor disasters, signal loss through the building occurs. The signal strength is small, and to efficiently handle the signal, the UAV's movement is essential. In disasters, the UAV should serve various users at least once. On that assumption that various users can be serviced even once, then, the UAV should consider the order of user processing based on the scenario's requirements. Therefore, in this section, we propose a table-based fair transmission algorithm that can serve various users at least once. We further propose a UAV movement selection algorithm using Lyapunov optimization that selects UAV movements based on the scenario's requirements.

### A. THE TABLE-BASED FAIR TRANSMISSION ALGORITHM

Let us consider a disaster. In such situations, receiving data from as many users as possible at least once is of the utmost

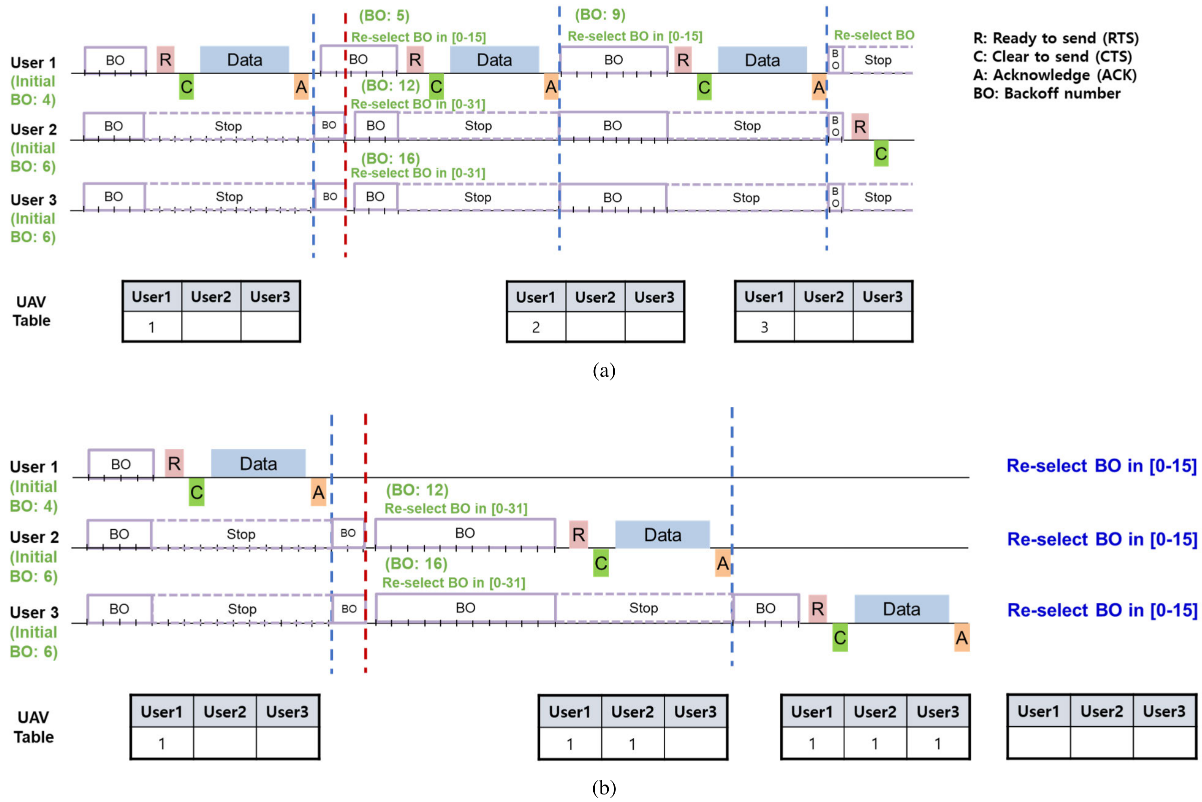


**FIGURE 4.** (a) The conventional CSMA protocol. (b) The CSMA protocol using table-based fair transmission algorithm.

importance. We assume that the carrier-sense multiple access with collision avoidance (CSMA/CA) is used for the data transmission procedure. This implies that users compete for channel allocation, and if one wins the competition, it tries to transmit data. If the transmitted signal's strength exceeds a certain threshold, the transmission is considered to be a success. In this case, for various users to transmit at least once or more, data transmission fairness must be guaranteed.

For this purpose, we propose a table-based fair transmission algorithm. The detailed procedure of the proposed algorithm is described in Algorithm 1. We assume that the UAV acquires the user's location through the initial flight. As a result, a unique user index is assigned based on the user's location. To facilitate this, the UAV creates a table with several columns equal to the total number of users. Fig. 3 describes acknowledgement (ACK) frame structure. Users include their user index information in additional data fields in the frame control. The UAV receives this information and updates the corresponding column in the table by setting it to 1. This signifies that a particular user has been transmitted to at least once. Consequently, these users are exempted from participating in the channel contention process, allowing other users to utilize the channel efficiently. Furthermore, when all columns in the table are filled with 1s, indicating that every user has been served, all nodes initiate a re-contention process by selecting the minimum contention window (CW) size. This ensures fair channel access for subsequent data transmissions. The complexity of algorithm 1 is $O(\mathcal{N})$ for creating the UAV table.

Fig. 4 describes the conventional CSMA procedure and the procedure using the proposed algorithm. Fig. 4 (a) presents the conventional CSMA procedure. Each user has an initial backoff number; each one then decreases it. When the number becomes zero, the user with the zero backoff number occupies the channel. In this figure, user 1 occupies the channel and data transmission is successful. Moreover, we created a UAV table with as many columns as the number of users to determine which user sends data. After the transmission of user 1 is complete, user 1 selects a new backoff number. Users 2 and 3 have collided due to the same backoff number. Users in conflict select a number in a range that is twice as large as the initial backoff number selection range. After that, user 1 also occupies the channel with the smallest number and transmits the data again. This method allows one user to continue transmitting the information. Therefore, it is inadequate for emergencies where transmission is required at least once for multiple users. Fig. 4 (b) presents the procedure using the proposed algorithm. User 1 has the smallest backoff number and the transmission succeeds. Users 2 and 3 choose a backoff number from a larger range due to the collision, which is the same as the previous algorithm. However, when user 1 transmits once, it does not participate in the channel contention,

**Algorithm 1** The Table-Based Fair Transmission Algorithm

**Initialization**: Number of users $N$, Limited time for rescue $T$, SNR threshold $\delta$, Transmission success time $T_{succ}$, Transmission failure time $T_{fail}$, Transmission collision time $T_{coll}$, $t = 0$
**Create table and available user list**:
Initialize $UAV_{table}$, $UE_{avail}$
**for** $i = 1$ **to** $N$ **do**
    $UAV_{table}[i] = i$
    $UE_{avail}[i] = i$
**end for**
**Competition for channel occupying**:
**while** $t \leq T$ **do**
    Nodes in $UE_{avail}$ compete with each other
    **if** $UAV_{table}[all] == 1$ **then**
        Initialize $UAV_{table}$, $UE_{avail}$
    **end if**
    **if** Node $i$ wins the channel competition **then**
        **if** $SINR[i] > \delta$ **then**
            $UAV_{table}[i] = 1$
            $t \mathrel{+}= T_{succ}$
            User $i$ transmit data to UAV
            User $i$ is excluded from the $UE_{avail}$
        **else**
            $t \mathrel{+}= T_{fail}$
        **end if**
    **else** // Collision occurs
        $t \mathrel{+}= T_{coll}$
    **end if**
**end while**

which also applies to other users that do not participate in the channel contention. Therefore, in the procedure, UAV tables are filled with 1s. Moreover, when all tables are filled, all users can again compete for channels with the initial CW. Through this process, we guarantee transmission fairness during disasters. Therefore, this proposed method serves various users in such environments.

### B. THE LYAPUNOV OPTIMIZATION-BASED ONLINE UAV POSITIONING ALGORITHM

In this section, we propose Lyapunov optimization-based adaptive UAV localization. The UAV's movement results in a trade-off between the throughput and service users on various floors. Although the above algorithm satisfies the fair transmission requirement in preparation for the rescue situation, it is independent of the throughput, which depends on the overall service speed and diversity according to the service nodes at various locations. Therefore, we consider the two following situations: (i) The UAV starts its flight at an altitude where many users exist. Then, the UAV hovers over the location for throughput maximization. (ii) The UAV starts its flight at an altitude where many users exist. Then, it changes its altitude to support users with various floors. We call this support user diversity. We adopt our model parameters to queue dynamics to apply the trade-off relationship [12]. The queue dynamics for the UAV's throughput and diversity considering its movements can be formulated as follows:

$$Q[t+1] = \max\{Q[t] - b[t], 0\} + a[t], \tag{12}$$

where $Q[t]$, $b[t]$, and $a[t]$ represent the queue-backlog size, throughput, and amounts of communication requirements of users at $t$, respectively. In our model, the queue backlog concerns the time due to an emergency, where we assume that the time limit for the initial rescue is 10 minutes, which is the life-or-death decision time of a heart attack. With guaranteed fairness, the purpose of the UAV's movements is to maximize the throughput while satisfying support user diversity within the rescue time. The mathematical optimization problem in Eq. (12) is formulated as:

$$\max: \lim_{t\to\infty} \sum\nolimits_{\tau=0}^{t-1} b[L[\tau]], \tag{13}$$

$$\text{s.t.} \lim_{t\to\infty} \frac{1}{t} \sum_{\tau=0}^{t-1} Q[\tau] < \infty \text{ (stability)}, \tag{14}$$

where $b[L[\tau]]$ is the throughput according to location $L$ at the unit time $\tau$. The proposed algorithm stabilizes the queue by supporting various users at various heights with the UAV movement.

Our UAV localization model for time-average throughput maximization with diverse user support is designed as follows [13]. The drift-plus-penalty (DPP) algorithm maximizes the time-average throughput subject to user diversity in Lyapunov optimization. The UAV has to continuously move and service the users. Therefore, stability has the same meaning as user diversity. The quadratic Lyapunov function in the DPP is defined as:

$$Ly(Q[t]) = \frac{1}{2}Q[t]^2. \tag{15}$$

Then, the one-slot conditional Lyapunov drift in slot t is expressed as follows:

$$\Delta Q[t] = \mathbb{E}[Ly(Q[t+1]) - Ly(Q[t]) | Q[t]]. \tag{16}$$

The Lyapunov drift pursues the DDP's upper bound for queue stability as follows:

$$\Delta Q[t] + V\mathbb{E}[-b(\alpha[t])], \tag{17}$$

where $V$ is the trade-off factor between the throughput and the stability (diversity).

The upper bound of the Lyapunov function's drift is expressed as follows:

$$\begin{aligned} &Ly(Q[t+1]) - Ly(Q[t]) \\ &= \frac{1}{2}Q[t+1]^2 - Q[t]^2 \\ &\leq \frac{1}{2}(a^2(\alpha[t]) + b^2(\alpha[t])) + Q[t](a(\alpha[t]) - b[t]) \end{aligned} \tag{18}$$

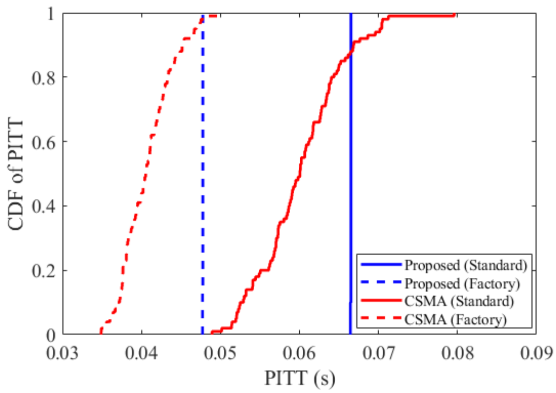


**FIGURE 5.** The PITT of two building types with the conventional algorithm.

Therefore, the conditional Lyapunov drift can be expressed as:

$$\Delta Q[t] = \mathbb{E}[Ly(Q[t+1]) - Ly(Q[t])|Q[t]] \\ \leq A + \mathbb{E}Q[t](a(\alpha[t]) - b[t]Q[t]), \tag{19}$$

where A is a constant. The Lyapunov function is the basic method in the analysis of asymptotic stability for ordinary differential equation [14]. Moreover, the minimization of the upper bound for the DPP minimizes the expectations, which can be minimized by $\alpha^*[t]$ at the current queue backlog Q[t] as follows:

$$\alpha^*[t] = \arg \min_{\alpha[t]\in A} [-Vb[L[t]] + Q[t]a(\alpha[t])]. \tag{20}$$

Then, our model observes the throughput covered by the UAV at a specific location, and decides whether to move or hover. Finally, the optimal selection $\alpha^*[t]$ has a trade-off coefficient $V$ expressed as:

$$\alpha^*[t] = \max : V \cdot b[L[t]] - Q[t] \cdot a[t]. \tag{21}$$

Consequently, the UAV adaptively selects movements to maximize the throughput under the user diversity guarantee based on the disaster situation. Moreover, the Lyapunov optimization-based online UAV positioning algorithm has computational complexity of $O(\mathcal{N})$ according to the number of possible selections $\alpha[t]$. Therefore, the total computational complexity of the algorithms proposed in this paper becomes $O(\mathcal{N})$.

## IV. PERFORMANCE EVALUATION

### A. SIMULATION ENVIRONMENTS

We evaluated the proposed model using the *DJI Phantom4 Pro v2.0 UAV* parameters by simulating it. The specifications based on IEEE 802.11 standards [15] are summarized in Table 1. We assumed that 100 nodes are spread in the building where the cellular network is disrupted due to the disaster. To compare the throughput performance, most nodes (approximately 30 nodes) were located on the 8 *th* floor (24 *m*). It is necessary to serve as many nodes as possible during disasters; thus, we used quadrature phase-shift keying (QPSK) with a low SNR threshold with a 19.5 *Mbps* of data rate [16].

**TABLE 1.** Simulation parameters.

| Parameter | Value | Parameter | Value |
|---|---|---|---|
| PHY header | 20 $\mu s$ | Building height | 50 m |
| PHY preamble | 16 $\mu s$ | Building width | 60 m |
| PHY signal | 4 $\mu s$ | Building depth | 15 m |
| RTS size | 20 bytes | Floor height | 5 m |
| CTS & ACK size | 14 bytes | Bandwidth | 20 MHz |
| Payload size | 1500 bytes | Frequency | 5 GHz |
| SIFS | 16 $\mu s$ | $P_{UAV}$ | 30 dBi |
| DIFS | 34 $\mu s$ | $P_{Node}$ | 20 dBi |
| Slot time | 9 $\mu s$ | $CW_{min,max}$ | [15, 1023] |

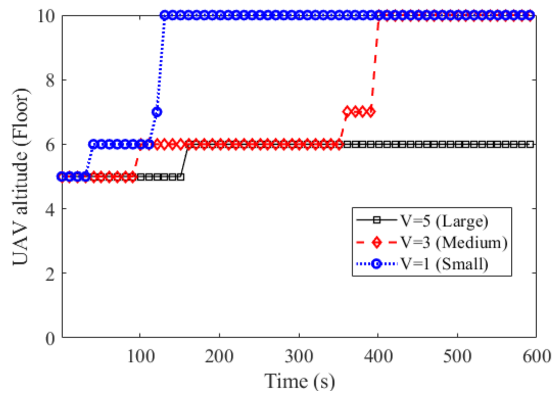


**FIGURE 6.** A selection of UAV movements with a varying ***V*** in a standard-type building.

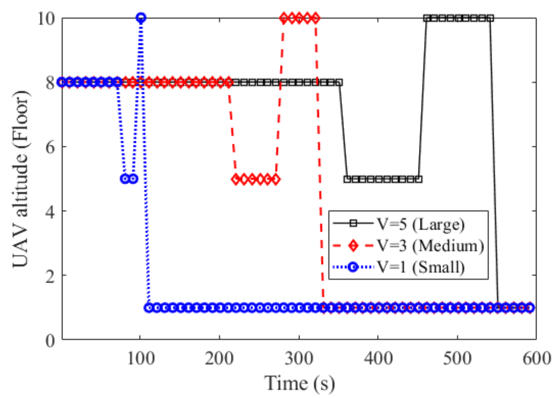


**FIGURE 7.** A selection of UAV movements with a varying ***V*** in a factory-type building.

### B. RESULTS AND DISCUSSION

Fig. 5 shows the cumulative distribution function (CDF) of the packet inter-transmission time (PITT) for fairness performance. We calculated the PITT of user $i$ as follows:

$$PITT_i = T/S_i, \tag{22}$$

where the $T$ is the total time steps and the $S_i$ is the number of frames where user $i$ transmits data. PITT refers to the time required for a node to transmit the next packet after transmitting the previous one. In this case, the closer the PITT's CDF to the vertical is, the higher the fairness. This is because the node's transmission time interval is constant. In Fig. 5, the blue line indicates the proposed fair transmission algorithm while the red line is the conventional CSMA one. Additionally, the solid line represents a standard type building, and the dotted line represents a factory-type one. The proposed algorithm demonstrates the results of sending a fairer transmission. Moreover, since the standard type building did not consider the floor loss, it had a higher signal strength and showed a higher transmission attempt probability. Therefore, more nodes transmit for a limited time and each one has a longer PITT time than a factory-type building that does not have more opportunities to transmit.

Figs. 6 and 7 depict the UAV altitude selection using the Lyapunov optimization algorithm according to time with various $V$ and with two building types. Fig. 6 shows the UAV movement selection with no floor loss within the standard building type, and Fig. 7 demonstrates it with the factory-type building. In this figure, the y-axis indicates the specific floor where the UAV is present. Thus, height variance implies that the UAV moves to other floors to support other nodes. The proposed algorithm adaptively selects whether to move or hover because the UAV must decide whether to serve '*several people at a high throughput*' or '*several people on a diverse floor*' within the emergency time (10 minutes). As shown in the blue circle, as $V$ becomes smaller, the selection tends to update itself based on the movements to serve people on varying floors. The model with a smaller $V$ focused on people on varying floors that could communicate with the UAV. In contrast, a large $V$ supported the most crowded floor (51 nodes on the $8th$ floor), which has the highest throughput in the factory type. For a model that focuses on throughput without user diversity, it is advantageous to hover the most over a crowded floor. However, in the standard building type, the UAV starts on the $5th$ floor instead of the one where there are many nodes. This is because since it does not consider the floor penetration loss, it is possible to serve many users on the floor below and above when it is on the $5th$ floor compared to a factory-type building that has restrictions on serving users with the floor.

Fig. 8 shows the comparison our proposed algorithm with conventional CSMA protocol when UAV moves according to the Lyapunov constant $V$ in two building types. The y-axis indicates number of served nodes out of 100 nodes. The graph is divided into three groups according to the degree of $V$. The left group means the blue graph in Figs. 6 and 7 above when $V$ is small. The right bars are when $V$ is large. The blue bar among the 4 bars in Fig. 8 is the number of nodes that can be served when UAV moves to the path obtained through Lyapunov using the proposed algorithm in standard-type building. The orange bar is conventional CSMA protocol in standard-type building. The yellow and purple bars are on the factory-types. The blue and yellow bars using the proposed algorithm serve all 100 nodes at least once when $V$ are small and medium. In the orange bar using CSMA in

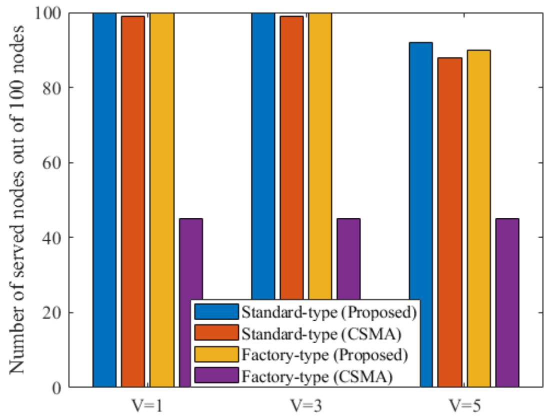


**FIGURE 8.** Number of served nodes out of 100 nodes with varying $V$.

**TABLE 2.** Performance comparison with conventional algorithms.

| Environment | Algorithm | | Throughput (Mbps) | Jain's index |
|---|---|---|---|---|
| Factory-type | Proposed algorithm | V=1 | 4.216 | 1 |
| | | V=3 | 4.517 | 1 |
| | | V=5 | 5.042 | 1 |
| | Conventional MAC protocol | V=1 | 12.915 | 0.348 |
| | | V=3 | 12.938 | 0.676 |
| | | V=5 | 12.953 | 0.890 |
| | PSO [17] | | 5.417 | 0.45 |
| Standard-type | Proposed algorithm | V=1 | 8.912 | 1 |
| | | V=3 | 9.870 | 1 |
| | | V=5 | 10.823 | 1 |
| | Conventional MAC protocol | V=1 | 12.977 | 0.109 |
| | | V=3 | 12.981 | 0.073 |
| | | V=5 | 12.982 | 0.116 |
| | PSO [17] | | 10.91 | 0.99 |

the standard-type, the number of nodes is slightly less than the proposed algorithm. Moreover, the purple bar in factory-type can served less nodes than standard-type. This is because factory-type buildings have more severe signal attenuation than standard-type buildings. In large $V$, it has a similar shape to other $V$, however, the proposed algorithm cannot serve all nodes because the rate considering the throughput increases in large $V$, thus, UAV has a lot of time fixed at one location. Consequently, our proposed algorithm adaptively changes the UAV's height to achieve optimal user service at the appropriate $V$.

Table. 2 shows the performance comparison of our proposed algorithm with conventional algorithms in terms of throughput and fairness. The particle swarm optimization (PSO) is used for conventional algorithm in [6] and [17]. The PSO algorithm updates the UAV location by local solution and global solution that construct velocity of particles. The equation of velocity for update as follows:

$$v_i^{t+1} = wv_i^t + c_1 r_1 (p_i^t - x_i^t) + c_2 r_2 (g^t - x_i^t),$$
$$i = 1, 2, \ldots, S, t = 1, 2, \ldots, K \qquad (23)$$

where $S$ indicates the number of particles; $K$ means the largest number of iterations; $w$ is an weight value against velocity at $t$; $c_1, c_2$ is are learning rate that can control proportion to optimal position between local and global location; $r_1$ and $r_2$ are random numbers in [0, 1]; $p_i^t$ and $g^t$ are local and global optimal position which maximize object function and they are updated whenever a new location come out to be close solution. Each $i_{th}$ particle position $x_i^t$ at $t$ updates velocity until all particles have the same values. Moreover, the throughput, which is an indicator of receiving many rescue signals for a limited time, and the fairness of user signal reception are analyzed using the Jain's fairness index [18]. The Jain's fairness index can be represented as follows:

$$f = \frac{(\sum_{i=1}^{N} t_i)^2}{N \sum_{i=1}^{N} (t_i)^2}, \tag{24}$$

where $f$ is fairness index. $N$ and $t_i$ are the number of users and throughput of user $i$, respectively. The fairness index value is determined from 0 to 1. The closer to 1, the higher the fairness, and the worst case is when the fairness index value is $\frac{1}{N}$.

In Table. 2, Jain's index of proposed algorithm is higher than that of conventional algorithm in both standard and factory types. This is because UAV serves node at fixed point in PSO algorithm and we use the table-based fair transmission algorithm. However, UAV can serve many nodes at various points using Lyapunov optimization. Moreover, UAV can serve only 45 users in factory-type building using PSO by fixed location. In all the case of Table. 2, throughput performance in standard-type is higher than factory-type by the floor penetraion loss.

## V. CONCLUSION

This paper proposed an optimal UAV localization algorithm to maximize user service in an indoor disaster environment. Additionally, we proposed the table-based fair transmission algorithm to fairly support various users. Moreover, we determined the optimal UAV localization under various situations by formulating the communication time and user connectivity using Lyapunov optimization. Based on the simulation results, our proposed UAV placement algorithm showed various paths according to different scenarios considering the throughput or diversity. Furthermore, we considered two path-loss models according to the building type to consider practical indoor environments. Finally, we demonstrated that our model guarantees time-average user connectivity maximization in various requirement scenarios.

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**JUNGHWA KANG** (Student Member, IEEE) received the B.S. degree from the Department of Electrical and Computer Engineering, Ajou University, Suwon, South Korea, in 2021, where she is currently pursuing the M.S. degree with the Department of Artificial Intelligence Convergence Network. Her current research interests include optimization algorithm, reinforcement learning for UAV networks, and medium access control protocols. She was a recipient of the Best Paper Award at KICS 2022 Winter Conference, in 2022.

**KYEONGROK KIM** (Member, IEEE) received the B.S. degree in computer and telecommunications engineering from Yonsei University, Wonju, Republic of Korea, in 2013, and the M.S. degree in space electronics and information engineering and the Ph.D. degree in electrical and computer engineering from Ajou University, Suwon, Republic of Korea, in 2016 and 2022, respectively.

He has been a Senior Engineer with the Satellite System Team 1, Hanwha Systems, Yongin, Republic of Korea, since February 2022. His current research interests include the system design of micro satellite onboard SAR, SAR performance evaluation, and SAR image processing and applications. He was a recipient of the Best Paper Award by the Korean Institute of Communications and Information Sciences (KICS), in 2017 and 2022, the Best Paper Award by the Kang Award from Ajou University, in 2022, the IEEE VTS Seoul Chapter Award by APWCS, in 2019 and 2021, the Grand Paper Prize by KICS Haedong Best Paper Award, in 2021, the ICT Paper Contest Award by Electronic Times, in 2020, the Director of a Research Center Award by the Korea Electronics Technology Institute (KETI), in 2020, and the Bronze Paper Award from IEEE Seoul Section Student Paper Contest, in 2018.

**HOWON LEE** (Senior Member, IEEE) received the B.S., M.S., and Ph.D. degrees in electrical and computer engineering from the Korea Advanced Institute of Science and Technology (KAIST), Daejeon, South Korea, in 2003, 2005, and 2009, respectively. From 2009 to 2012, he was a Senior Research Staff/a Team Leader of the Knowledge Convergence Team, KAIST Institute for Information Technology Convergence (KI-ITC). Since 2012, he has been with the School of Electronic and Electrical Engineering and the Institute for IT Convergence (IITC), Hankyong National University (HKNU), Anseong, South Korea. He was a Visiting Scholar with the University of California at San Diego (UCSD), La Jolla, CA, USA, in 2018. His current research interests include B5G/6G wireless communications, ultra-dense distributed networks, in-network computations for 3D images, cross-layer radio resource management, reinforcement learning for UAV networks, unsupervised learning for wireless communication networks, and the Internet of Things. He was a recipient of the Joint Conference on Communications and Information (JCCI) 2006 Best Paper Award and the Bronze Prize at Intel Student Paper Contest, in 2006. He was also a recipient of the Telecommunications Technology Association (TTA) Paper Contest Encouragement Award, in 2011, the Best Paper Award at the Korean Institute of Communications and Information Sciences (KICS) Summer Conference, in 2015, the Best Paper Award at the KICS Fall Conference, in 2015, the Honorable Achievement Award from 5G Forum Korea, in 2016, the Best Paper Award at the KICS Summer Conference, in 2017, the Best Paper Award at the KICS Winter Conference, in 2018, the Best Paper Award at the KICS Summer Conference, in 2018, and the Best Paper Award at the KICS Winter Conference, in 2020. He received the Minister's Commendation by the Minister of Science and ICT, in 2017.

**JAE-HYUN KIM** (Member, IEEE) received the B.S., M.S., and Ph.D. degrees in computer science and engineering from Hanyang University, Ansan, South Korea, in 1991, 1993, and 1996, respectively. In 1996, he was with the Communication Research Laboratory, Tokyo, Japan, as a Visiting Scholar. From April 1997 to October 1998, he was a Postdoctoral Fellow with the Department of Electrical Engineering, University of California at Los Angeles. From November 1998 to February 2003, he was a member of Technical Staff with the Performance Modeling and QoS Management Department, Bell Laboratories, Lucent Technologies, Holmdel, NJ, USA. Since 2003, he has been with the Department of Electrical and Computer Engineering, Ajou University, Suwon, South Korea, as a Professor. His research interests include medium access control protocols, QoS issues, cross layer optimization for wireless communication, satellite communication, and mobile data offloading. He is currently the Center Chief of the Satellite Information Convergence Application Services Research Center (SICAS) sponsored by the Institute for Information and Communications Technology Promotion, South Korea. He has been the Chairman of the Smart City Committee of 5G Forum in South Korea, since 2018. He is the Vice Chairman of the Korea Institute of Communication and Information Sciences (KICS). He is a member of the KICS, the Institute of Electronics and Information Engineers, and the Korea Information Science Society.