IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 20 April 2024, accepted 22 May 2024, date of publication 5 June 2024, date of current version 13 June 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3409779

RESEARCH ARTICLE

HyPE: Online Hybrid Pseudo-Bayesian Estimation Method for S-ALOHA-Based Tactical FANETs

JIMIN JEON[1], (Student Member, IEEE), JUNSEUNG LEE[2,3], (Student Member, IEEE), TAEWOOK KIM[1], (Student Member, IEEE), JAEHA AHN[4], YOUNGBIN YU[5], MIN LEE[5], HEEJUNG YU[6], (Senior Member, IEEE), AND HOWON LEE[7], (Senior Member, IEEE)

[1]Department of AI Convergence Network, Ajou University, Suwon 16499, South Korea
[2]School of Electronic and Electrical Engineering, Hankyong National University, Anseong 17579, South Korea
[3]Research Center for Hyper-Connected Convergence Technology, Hankyong National University, Anseong 17579, South Korea
[4]Agency for Defense Development, Daejeon 34186, South Korea
[5]LIG Nex1, Yongin 16911, South Korea
[6]Department of Electronics and Information Engineering, Korea University, Sejong 30019, South Korea
[7]Department of Electrical and Computer Engineering, Ajou University, Suwon 16499, South Korea

Corresponding authors: Howon Lee (howon@ajou.ac.kr) and Heejung Yu (heejungyu@korea.ac.kr)

This work was supported by the Defense Acquisition Program Administration (DAPA) and the Agency for Defense Development (ADD) under Grant UG223047VD.

ABSTRACT Significant challenges are involved in tactical flying ad-hoc network (FANET) missions because network environments are very dynamic. In addition, energy-efficient network operation is important in tactical FANETs owing to the limited capacity of the on-board battery in unmanned aerial vehicles (UAVs). In a slotted-ALOHA (S-ALOHA)-based tactical FANET, frequent packet collisions due to changes in the network environment deteriorate the energy efficiency. Therefore, accurately estimating the number of active UAVs is crucial for improving the performance of S-ALOHA-based networks. Several estimation methods such as low-bound, Schoute, max-probability, and Bayesian estimation have been studied, and these methods perform well in static network environments; however, the estimation error significantly increases in dynamic network environments. To accurately estimate the number of active UAVs in highly dynamic environments, this study proposes an online hybrid pseudo-Bayesian estimation (HyPE) method. Specifically, this method combines the pure-Bayesian and pseudo-Bayesian estimation methods to overcome their shortages such as the inability in a dynamic environment of the pure-Bayesian method and the low estimation accuracy of the pseudo-Bayesian method. This paper compares the performance of the proposed HyPE method with that of benchmark methods in terms of the estimation error according to the variation period and variation step size. The results show that HyPE is more adaptable to dynamic changes in network environments.

INDEX TERMS Bayesian estimation, unmanned aerial vehicle (UAV), active UAV, slotted-ALOHA, tactical flying ad-hoc network (FANET).

I. INTRODUCTION

Compared with the existing terrestrial networks, the flying ad-hoc network (FANET) is emerging as a promising technology because of its various advantages, such as high flexibility, cost efficiency, and adaptability. The FANET is a wireless communication network composed of unmanned aerial vehicles (UAVs), where UAVs communicate with each other without a permanent infrastructure to exchange flight and control information and collect data [1], [2], [3], [4], [5], [6]. FANETs play a crucial role in various aerial applications such as military services, monitoring of agricultural areas, disaster monitoring, and civil construction [7], [8], [9], [10], [11], [12], [13]. In particular, a tactical FANET must accomplish mission-critical military tasks in highly dynamic network environments. However, owing to the limited capacity of the on-board battery of UAVs, FANETs have a short lifetime; thus, energy-efficient network operation is critical [14], [15], [16], [17], [18], [19]. In addition, topological dynamics inherent to the high-speed movement

The associate editor coordinating the review of this manuscript and approving it for publication was Xijun Wang.

of UAVs and data traffic diversity cause rapid changes in the surrounding environment, resulting in inefficient radio resource utilization [20], [21], [22]. Even in a slotted-ALOHA (S-ALOHA)-based tactical FANET, frequent packet collisions caused by changes in the network environment may make it difficult for UAVs to complete their missions. These issues can be resolved by controlling the transmission probability of each active UAV effectively, which can be adjusted by accurately estimating the number of active UAVs.

Several studies have been conducted to estimate the number of active tags in radio-frequency identification (RFID) systems. The low-bound [23] and Schoute [24] methods estimate the number of active tags based on the numbers of collision slots and success slots of the previous frame. However, these methods still have a high error rate because of the inaccuracy in the number of tags that transmit packets in collision slots. The maximum probability (max-probability) method [25] estimates the number of active tags using a posterior probability distribution based on the events of the previous frame. Because the current estimation is based on the events of the previous frame, the estimation error gradually increases as the number of tags continuously changes. In [26], Eom and Lee estimated the number of tags by multiplying the number of collision slots by a proportional factor to achieve the optimal performance of dynamic framed S-ALOHA (DFSA) in RFID systems. The length of the next frame was adjusted according to the estimated number of tags.

Even though these conventional estimation methods perform well in static network environments, they face challenges in accurate estimation with changes in the number of tags. Hence, a Bayesian estimation method has been studied to enhance estimation accuracy compared to these methods. In [27], Tong et al. estimated the number of RFID tags (η) using a pure-Bayesian estimation method. Specifically, the length of the next frame in the DFSA was determined using the expected value of the estimated η. In [28], Wu and Zeng estimated η using a risk function, where the types of risk functions were based on the mean square error, absolute error, and posterior probability. The optimal frame length was determined to maximize the channel utilization efficiency. In addition, Annur et al. utilized the number of tags estimated using the Bayesian method to determine the access probability of an S-ALOHA-based anti-collision protocol in RFID systems by setting it to $1/\eta_0$ [29]. This value was derived from the posterior probability distribution to maximize the probability of success. In [30], Liu et al. proposed a pseudo-Bayesian backoff method for unsaturated slotted systems. The estimation process was simplified by assuming the probability distribution of backlog size as a Poisson distribution. The access probability was then adjusted based on the estimated backlog size to maximize the system throughput. Furthermore, in [31], to minimize the access delay in S-ALOHA systems, Liu et al. devised a delayed pseudo-Bayesian estimation method to obtain the transmission probability of users. In this study, the delay in broadcasting the optimal transmission probability at the base station (BS) was considered to control the transmission probability.

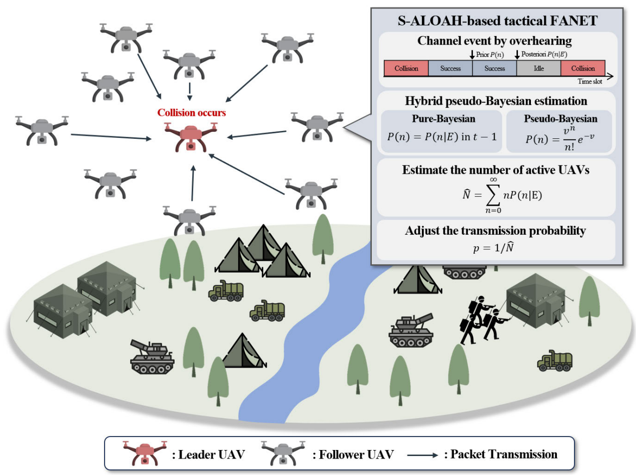


FIGURE 1. System model of the S-ALOHA-based tactical FANETs.

These Bayesian estimation methods can improve the estimation accuracy of the number of active users because they utilize specific channel status information in the previous and current frames in a probabilistic manner; however, these methods are difficult to adapt flexibly to variations in the number of users as they still use a cumulative probability distribution for the number of active users. Therefore, by combining the advantages of pure-Bayesian and pseudo-Bayesian methods, this paper proposes a new Hybrid Pseudo-Bayesian Estimation method (HyPE) that can adapt to changes in the FANET environment. Specifically, the proposed HyPE method initially utilizes an accumulated prior probability distribution, and in the pseudo-Bayesian phase, the accumulated prior probability distribution is reset to a Poisson distribution, which enables adaptability in environments with varying numbers of active UAVs. The main contributions of the proposed method are summarized as follows.

- This paper addresses the challenge of estimating the number of active UAVs in dynamic environments, such as tactical FANETs. The proposed HyPE combines pure-Bayesian and pseudo-Bayesian methods to offer accurate estimations, overcoming the limitations of each approach when used separately.
- In S-ALOHA, the estimated number of active UAVs can be used to determine the packet transmission probability. The well-determined transmission probability effectively minimizes collisions among multiple active UAVs, reducing unnecessary packet retransmissions. Optimizing the transmission probability can, therefore, maximize the throughput of S-ALOHA-based tactical FANET.
- Even if there is an estimation error, efficient resource allocation can be achieved by considering margins in advance. However, for more efficient resource utilization, accurate estimation is crucial. Through HyPE,

efficient resource utilization by estimating the number of active UAVs accurately can be achieved.

- In this study, to evaluate the performance of the proposed HyPE, low-bound, Schoute, max-probability, pure-Bayesian, and pseudo-Bayesian methods are considered benchmark methods. Through simulations, the robustness of the proposed method is verified by showing the superiority in simulation results depending on changes in factors such as the maximum number of active UAVs, variation period, variation threshold, and pseudo-Bayesian update period.

The remainder of this paper is organized as follows: Section II describes the system model and the proposed HyPE method for a tactical FANET environment. Section III presents various simulation results, demonstrating the excellent performance of HyPE compared with that of benchmark methods. Finally, in Section IV, conclusions are drawn.

II. SYSTEM MODEL AND PROPOSED METHOD

A. SYSTEM MODEL

This study considers an S-ALOHA-based tactical FANET, where all active follower UAVs have packets to transmit to the leader UAV, as shown in Figure 1. Follower UAVs can transmit packets every time slot, and packet transmission is attempted according to the packet transmission probability of each UAV.

At this time, it is assumed that all follower UAVs can overhear the packet transmission of neighbor UAVs and adjust their transmission probability by estimating the number of active UAVs. The individual calculation of the transmission probability based on overhearing can efficiently reflect the characteristics of the aerial network environment. In tactical FANETs, UAV mobility leads to operational accidents, mission-related losses, and interactions with other UAV formations, resulting in variability in the composition of the formation. Since the number of UAVs changes and cannot be accurately known, it is important to estimate the number of UAVs for the increase in the throughput in S-ALOHA. If the estimated number of UAVs is too large or too small for the actual number of UAVs, the throughput may eventually decrease. Therefore, this study estimates the number of UAVs by channel access event information and determines the packet transmission probability of each UAV using this estimated value. Specifically, the channel access event (E) is classified as success (S), collision (C), or idle (I). Success refers to a case in which only one UAV attempts to transmit in a specific slot, idle means that no one transmits, and collision implies that two or more UAVs attempt to transmit simultaneously. In this study, the actual and estimated numbers of active UAVs in time slot t are denoted as $N(t)$ and $\hat{N}(t)$, respectively. The other parameters used in this study are summarized in Table 1.

B. CONVENTIONAL BAYESIAN ESTIMATION METHODS

When the number of active follower UAVs is unknown by each UAV, pure-Bayesian and pseudo-Bayesian estimation methods can be used to estimate the number of active UAVs.

TABLE 1. Notation summary.

Notation	Description
$N(t)$	Actual number of active UAVs in time slot t
$\hat{N}(t)$	Estimated number of active UAVs in time slot t
p	Transmission probability
ϵ	Pseudo-Bayesian update period
ν_{th}	Variation threshold
E	Channel access event
S	Success event
I	Idle event
C	Collision event
$\bar{S}$	Number of success slots
$\bar{I}$	Number of idle slots
$\bar{C}$	Number of collision slots
α	Variation step size
β	Variation period
N_{min}	Minimum number of active UAVs
N_{max}	Maximum number of active UAVs

1) PURE-BAYESIAN ESTIMATION METHOD [29]

In the pure-Bayesian estimation method, the posterior probability $P(n|E)$ of the number of estimated active UAVs when E are given, can be expressed as

$$P(n|E) = \frac{P(E|n)P(n)}{P(E)}. \tag{1}$$

Here, $P(E|n)$ can be expressed as

$$P(E|n) = \binom{n}{k}(p)^k(1-p)^{n-k}. \tag{2}$$

Equation (2) expresses the probability of each event when the estimated number of active UAVs is n. Specifically, the probability of an idle slot (P_I) is calculated as $P_I = (1-p)^n$, the probability of a success slot (P_S) as $P_S = np(1-p)^{n-1}$, and the probability of a collision slot (P_C) as $P_C = 1 - P_I - P_S$, where p represents the transmission probability. In addition, $P(E)$ represents the total probability of E for all possible n, which can be expressed as

$$P(E) = \sum_{n=0}^{\infty} P(E|n)P(n). \tag{3}$$

In Equation (3), $P(n)$ represents the prior probability that the estimated number of active UAVs is n, where $P(n)$ is updated to $P(n|E)$ in the previous time slot. In this process, the probability distribution, initially equal to the likelihood of all active UAVs, converges to a specific number of active UAVs since the active UAVs are estimated based on the accumulated prior probabilities during the previous slots. This characteristic suits a static environment, but accurate

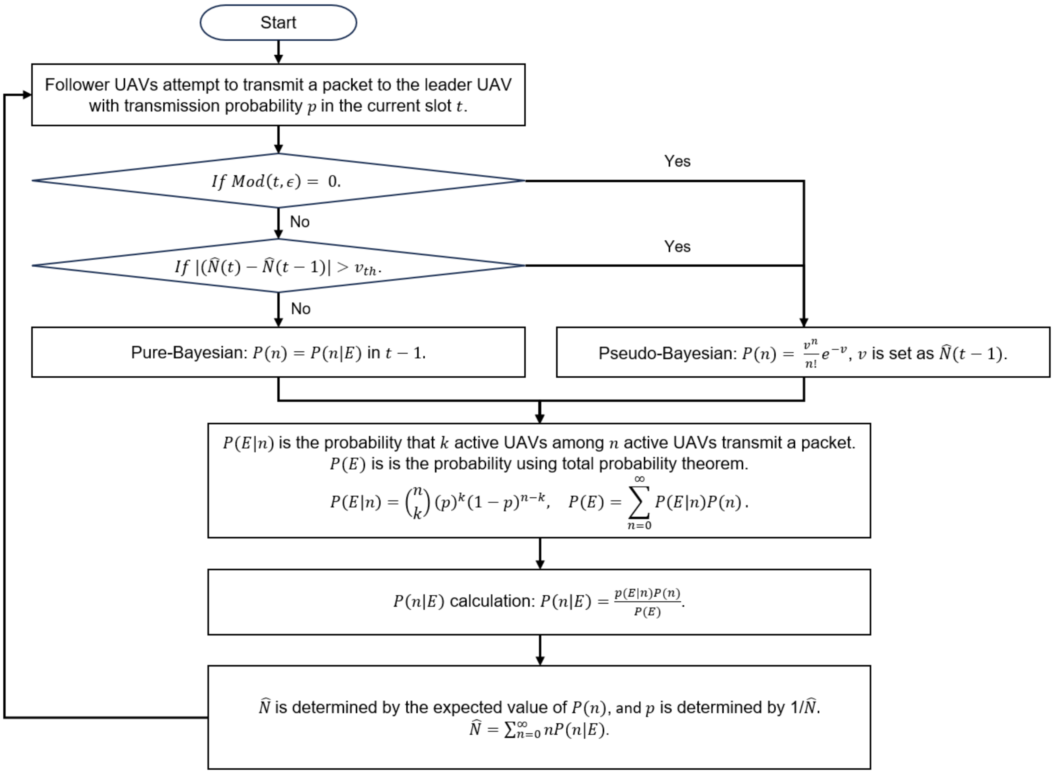


FIGURE 2. **Signaling flow of the proposed HyPE method.**

estimation is difficult when the number of active UAVs is very dynamic. Unfortunately, this pure-Bayesian estimation method calculates $P(n)$ for all n in every slot, which results in a significant computational burden for each UAV. Using Equation (1), the estimated number of active UAVs is calculated as $\hat{N}_{PB}(t) = \sum_0^{\infty} n \times P(n|E)$.

2) PSEUDO-BAYESIAN ESTIMATION METHOD [30]

To relieve the computational complexity of the pure-Bayesian estimation method, the pseudo-Bayesian estimation method assumes that the prior probability $P(n)$ is a Poisson distribution. The pseudo-Bayesian estimation method assumes that the prior probability $P(n)$ is a Poisson distribution to relieve the computational complexity of the pure-Bayesian estimation method. Assuming a Poisson distribution for the prior probability can simplify the estimation process by reducing the complexity of storing and updating the distribution of n in each time slot. Instead of exploiting the accumulated overall prior probabilities, only the average parameter (ν) of the Poisson distribution needs to be calculated and updated, which increases computational efficiency. In this method, $P(n)$ can be represented as follows:

$$P(n) = \mathbb{P}(n, \nu) = \frac{\nu^n}{n!}e^{-\nu}. \tag{4}$$

where ν means the average of the Poisson distribution and is set as the expected value of the estimated number of active UAVs in the previous slot. In addition, in each slot, ν is calculated according to E as follows:

$$\nu = \begin{cases} \nu - 1, & \text{if } E = I, \\ \nu, & \text{if } E = S, \\ \nu + 2.3922, & \text{if } E = C. \end{cases} \tag{5}$$

From Equation (5), if $E = I$, the estimated value is assumed to be greater than the actual value and ν is decreased. If $E = S$, the estimated value is assumed to be accurate; thus, the current value is maintained. Finally, if $E = C$, the estimated value is smaller than the actual value, and thus ν is increased by 2.3922. The increased value of 2.3922 is calculated using the Schoute method [24] as follows:

$$P(k|C) = \begin{cases} 0, & \text{if } k = 0, 1, \\ \dfrac{P_k}{1 - P_0 - P_1}, & \text{if } k \geq 2, \text{ where } P_k = e^{-1}/k!. \end{cases} \tag{6}$$

$$\sum_{k=2}^{\infty} kP(k|C) = \frac{\sum_{k=2}^{\infty} e^{-1}\frac{1}{(k-1)!}}{1 - 2e^{-1}} = \frac{e-1}{e-2} \approx 2.3922. \tag{7}$$

Here, P_k is the probability that k UAVs will transmit packets, and the number of active UAVs in the collision slot can be obtained from the conditional expected value for $P(k|C)$. Consequently, ν is increased by 2.3922 when $E = C$. When

$E = I$, an idle event represents an overestimation of the number of active UAVs, and ν is decreased by 1 [30].

Because the pseudo-Bayesian estimation method uses a Poisson distribution to obtain $P(n)$, this method has an advantage in terms of computational complexity compared with the pure-Bayesian estimation method, which calculates $P(n)$ for all possible n. In the pseudo-Bayesian method, the estimated number of active UAVs can be obtained simply using $\hat{N}_{SB}(t) = \nu$. However, unlike the pure-Bayesian method, the pseudo-Bayesian method continuously updates ν, which results in an error-divergence problem for the estimated value.

C. PROPOSED ONLINE HYBRID PSEUDO-BAYESIAN ESTIMATION (HYPE) METHOD

The pure-Bayesian method in Section II-B1 has the advantage of being able to show high estimation accuracy in environments, where the number of active UAVs is fixed because it updates the probability distribution for the number of active UAVs by accumulating it with events that occur in each slot. However, this method is not suitable for the environment under consideration in this study, in which the number of active UAVs is variable, because the probability distribution converges to a specific number of active UAVs when applying a pure-Bayesian method. To address this problem, the pseudo-Bayesian method described in Section II-B2 is useful, but as explained, the pseudo-Bayesian method may have a high estimation error due to the unstable probability distribution. Therefore, the HyPE method is proposed to overcome the drawbacks of pure-Bayesian and pseudo-Bayesian methods by alternating between the two methods depending on whether the criteria are met. This is explained in detail as follows: The proposed HyPE method estimates the number of active UAVs based on the prior probability distribution $P(n)$ for the estimated value n of the number of active UAVs. $P(n)$ is updated using $P(n|E)$ of the previous slot, as mentioned in the pure-Bayesian estimation method. To adapt to network dynamics in the tactical FANET environment, when update criteria are satisfied, the HyPE method updates $P(n)$ using the Poisson distribution with the mean value, ν, which is the estimated number of active UAVs in the previous slot. As update criteria, $\mathrm{Mod}(t, \epsilon) = 0$ and $|\hat{N}(t) - \hat{N}(t-1)| > \nu_{th}$ are utilized. Here, t is the slot index, ϵ is the pseudo-Bayesian update period, and ν_{th} represents the update threshold. Even though it is optimal to set the update criteria, such as ϵ or ν_{th}, to precisely match actual traffic variations, this is nearly impractical. Therefore, update criteria can be set to the average of past traffic changes. Consequently, $\hat{N}(t)$ is calculated as $\hat{N} = \sum_0^\infty n \times P(n|E)$. Using $\hat{N}(t)$, the transmission probability of active UAV i is determined as $p(t+1) = 1/\hat{N}(t)$ to improve the network performance. The detailed operational procedure is shown in Figure 2 and Algorithm 1.

Algorithm 1 Detailed Operational Procedure of HyPE

for $t = 1, 2, \ldots$ **do**
  Follower UAVs transmit a packet to the leader UAV with transmission probability p in time slot t.
  for $i = 1, 2, \ldots$ **do**
    UAV i has information on channel access events.
    UAV i calculates $P(n)$ as follows:
    if ($\mathrm{Mod}(t, \epsilon) = 0$) or ($|(\hat{N}(t-1) - \hat{N}(t-2)| > \nu_{th}$) **then**
      $P(n) = \frac{\nu^n}{n!} e^{-\nu}$, ν is set as $\hat{N}(t-1)$.
    else
      $P(n) = P(n|E)$ in $t-1$.
    end if
    UAV i calculates $P(E|n)$ from Equation (2).
    UAV i calculates $P(E)$ from Equation (3).
    UAV i calculates $P(n|E)$ using $P(E|n)$, $P(E)$, and $P(n)$ from Equation [PnE](1).
    UAV i estimates the number of active UAVs in time slot t as $\hat{N}(t) = \sum_0^\infty n \times P(n|E)$.
    UAV i determines its transmission probability in time slot $t+1$ from $p(t+1) = 1/\hat{N}(t)$.
  end for
end for

III. PERFORMANCE EVALUATION

This study considered S-ALOHA-based tactical FANET environments and simulations were conducted using MATLAB on a computer with an i5-12600 CPU (3.30 GHz) and 32.0 GB of RAM. To analyze the performance of the benchmark and proposed methods, the error function for estimation ($f(N, \hat{N})$) was applied, which can be defined as follows:

$$f(N, \hat{N}) = \left| \frac{N - \hat{N}}{N} \right| \times 100 \, [\%]. \tag{8}$$

In this section, the initial number of active UAVs is set to 30, and the minimum number (N_{min}) and maximum number (N_{max}) are set to 10 and 50, respectively. For each variation period (β), up to α UAVs can enter or leave the network, where α and β are set to 5 [UAVs] and 50 [slots], respectively. Here, α is the variation step size of the number of active UAVs. In addition, the pseudo-Bayesian update period (ϵ) and variation threshold (ν_{th}) for the proposed HyPE method are configured as 50 and 10, respectively. To evaluate the performance accurately, Figure 3 is the result of 2000 slots in a particular traffic change environment, and Figures 4, 5, and 6 are the results of 1,000 iterations consisting of 2,000 slots.

A. BENCHMARK METHODS

This section presents three benchmark methods for comparing the performance of the proposed method. The following section provides a detailed description of the three benchmark methods used to estimate the number of active UAVs.

- **Low-bound method**: This method estimates the number of active UAVs using the number of success slots ($\bar{S}$) and collision slots ($\bar{C}$) that occurred among the previous

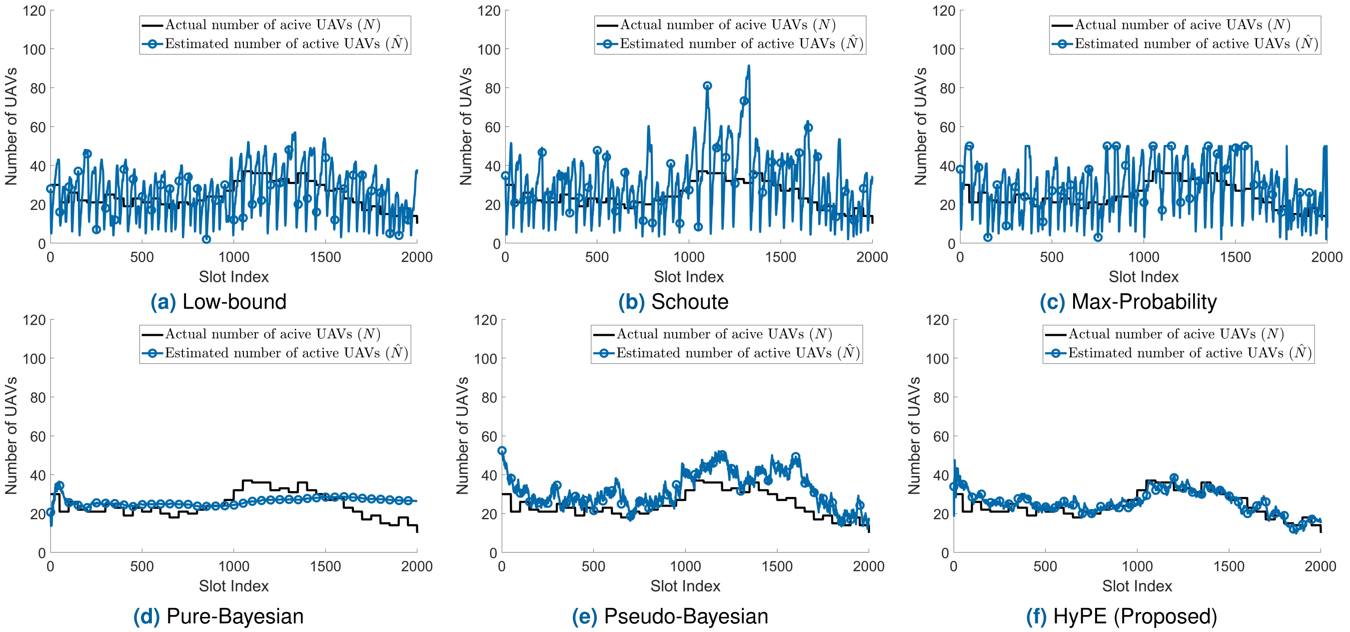


FIGURE 3. Actual number of active UAVs ($N(t)$) and estimated number of active UAVs ($\hat{N}(t)$) under $\alpha = 5$ and $\beta = 50$ in tactical FANET environments.

$\hat{N}(t-1)$ slots. Here, $\hat{N}(t-1)$ denotes the estimated number of active UAVs in the previous slot. Each active UAV transmits a packet at a transmission probability set to $1/\hat{N}(t-1)$. If a collision occurred in a specific slot, it means that at least two UAVs transmitted packets. Thus, this method estimates the number of active UAVs as $\hat{N}(t) = \bar{S} + 2\bar{C}$.

- **Schoute method**: This method estimates the number of active UAVs using the $\bar{S}$ and $\bar{C}$ that occurred among the previous $\hat{N}(t-1)$ slots. The transmission probability for each active UAV is determined as $1/\hat{N}(t-1)$. Unlike the low-bound method, the Schoute method calculates the number of active UAVs in the collision slot from Equation (6) and Equation (7). Consequently, this method estimates the number of active UAVs as $\hat{N}(t) = \bar{S} + 2.3922\bar{C}$.
- **Max-probability method**: In this method, the number of active UAVs can be estimated using the following equations (9), as shown at the bottom of the page, and (10).

$$\hat{N}(t) = \arg\max_{n} P(n|\bar{I}, \bar{S}, \bar{C}). \tag{10}$$

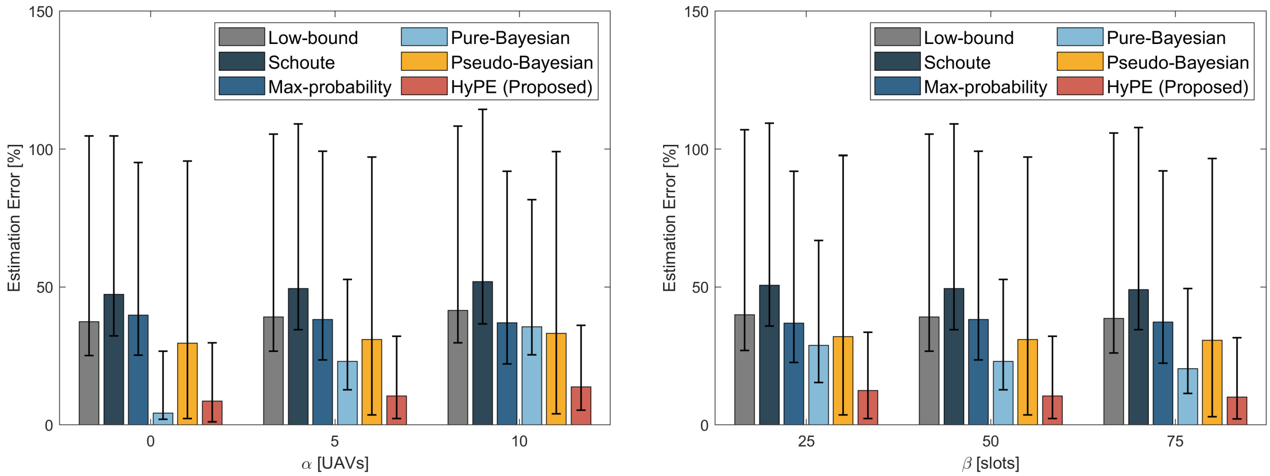
From these equations, the max-probability method estimates the number of active UAVs through n maximizing $P(n|\bar{I}, \bar{S}, \bar{C})$ given $\hat{N}(t-1)$, $\bar{I}$, $\bar{S}$, and $\bar{C}$, where the transmission probability for each active UAV in the max-probability estimation method (p_M) is set to $1/\hat{N}(t-1)$.

The low-bound, Schoute, and max-probability methods estimate the number of active UAVs on a frame-by-frame manner based on the information about events that occurred in the previous frame. However, since this study performs slot-by-slot estimation, it is not suitable to directly apply the benchmark method devised based on a frame-by-frame manner. Therefore, the low-bound, Schoute, and max-probability methods are assumed to estimate the current number of active UAVs by identifying events in previous slots equal to the estimated number of active UAVs.

B. SIMULATION RESULTS

Figures 3(a)–3(f) show the actual and estimated numbers of active UAVs for the proposed and benchmark methods according to the progress of the slot, respectively. The simulation was conducted under $\alpha = 5$ and $\beta = 50$. The low-bound, Schoute, and max-probability methods estimate the number of active UAVs based on the events that occurred in the previous $\hat{N}(t-1)$ slots, that is, the estimated number of UAVs in the $(t-1)th$ slot. Unlike the low-bound method, which estimates $\hat{N}(t)$ as $\bar{S} + 2\bar{C}$ in the previous $\hat{N}(t-1)$ slots, the Schoute method determines $\hat{N}(t)$ as $\bar{S} + 2.3922\bar{C}$. Also, it can be seen that $\hat{N}$ in the max-probability method does not exceed 50, because this method estimates the number of UAVs as the number with the largest $P(n|\bar{I}, \bar{S}, \bar{C})$,

$$P(n|\bar{I}, \bar{S}, \bar{C}) = \frac{(\hat{N}(t-1))!}{\bar{I}!\bar{S}!\bar{C}!} \times \left[(1-p_M)^n\right]^{\bar{I}} \times \left[\frac{n}{\hat{N}(t-1)}(1-p_M)^{(n-1)}\right]^{\bar{S}} \times \left[1-(1-p_M)^n - \frac{n}{\hat{N}(t-1)}(1-p_M)^{(n-1)}\right]^{\bar{C}}. \tag{9}$$



(a) Estimation error vs. α **(b)** Estimation error vs. β

FIGURE 4. Estimation error of the benchmark and proposed methods according to α and β.

which considers only n from 0 to N_{max}. As shown in Figures 3(d)–3(f), Bayesian estimation methods estimate the number of active UAVs more accurately because they determine $\hat{N}(t)$ by obtaining the posterior probability using the prior probability. The pure-Bayesian method is vulnerable to dynamic network environments, where the number of active UAVs is variable, because it performs an estimation based on the accumulated prior probability during the previous slots. In contrast to the pure-Bayesian method, the pseudo-Bayesian method obtains $\hat{N}(t)$ through a Poisson distribution with mean ν, where ν denotes the estimated number of active UAVs obtained from the previous slot. Thus, it is more adaptable to variations in the number of active UAVs. However, the estimation error of the pseudo-Bayesian method becomes relatively large because it utilizes an instantaneous Poisson distribution. In the proposed HyPE method, to compensate for the problem of the pure-Bayesian estimation method, $P(n)$ is updated using the pseudo-Bayesian estimation method when the update criteria $mod(t, \epsilon) = 0$ and $|\hat{N}(t) - \hat{N}(t-1)| > \nu_{th}$ are satisfied. As a result, compared with the benchmark methods, the proposed method can minimize the estimation error, even when the number of active UAVs is very dynamic.

Figures 4(a) and 4(b) show the estimation errors of the benchmark and proposed methods according to the variation step size (α) and variation period (β) in S-ALOHA-based tactical FANETs. Because the FANET topology is very dynamic, a large α and a small β result in an increase in the estimation error. In Figure 4(a), β is set to a fixed value of 50 and α takes various values such as 0, 5, and 10. As α increases, it can be observed that the estimation error increases in all methods except the max-probability method. When $\alpha = 10$, the low-bound, Schoute, and max-probability methods have relatively high estimation errors of 41.57 [%], 52.01 [%], and 37.09 [%], respectively. Moreover, because the low-bound and Schoute methods estimate the number of active UAVs simply using channel access events, the difference in performance degradation is not severe against an increase in α. However, the estimation errors are still higher than those of the other methods. Because the max-probability method determines the optimal n that maximizes $P(n|\bar{I}, \bar{S}, \bar{C})$, the estimation results may vary significantly depending on the combinations of $\{\bar{I}, \bar{S}, \bar{C}\}$. In addition, this method considers only the probability distribution for the number of active UAVs ranging from 0 to 50, and thus, estimation errors resulting from estimating beyond 50 are not taken into account. The pure-Bayesian method estimates the number of active UAVs based on the accumulated prior probability during the previous slots, resulting in a considerable increase in the estimation error as α increases. In particular, this method has the lowest estimation error of 4.34 [%] among all the methods when $\alpha = 0$, but a significantly higher estimated error of 35.6 [%] when $\alpha = 10$. In addition, because the pseudo-Bayesian method determines $\hat{N}(t)$ only from the channel access events in the previous slot, this method can better follow the variations in the number of active UAVs. However, the estimation error is relatively high. The proposed HyPE method has the best estimation accuracy and adaptability to variations in the number of active UAVs, with the lowest estimation errors of 10.59 [%] and 13.83 [%] when $\alpha = 5$ and $\alpha = 10$, respectively.

In Figure 4(b), α is set to a fixed value of 5 and β takes various values such as 25, 50, and 75. As β decreases, the estimation error of all the methods increases. In particular, when $\beta = 25$, the low-bound, Schoute, and max-probability methods show higher estimation errors than the proposed method, resulting in errors of 40.01 [%], 50.58 [%], and 36.92 [%], respectively. As mentioned previously, because the low-bound, Schoute, and max-probability methods estimate the number of active UAVs using only channel access events, the variation in the estimation errors is not severe

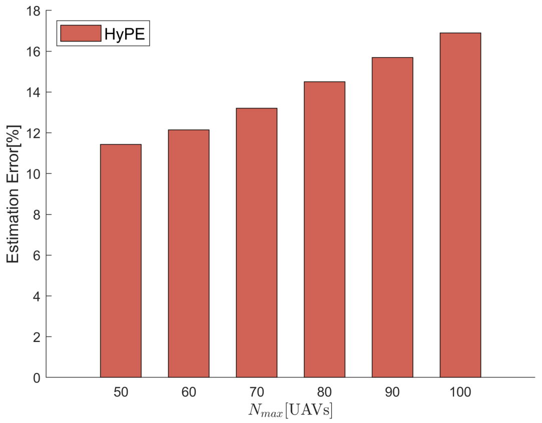


FIGURE 5. Estimation error of the proposed method according to N_{max}.

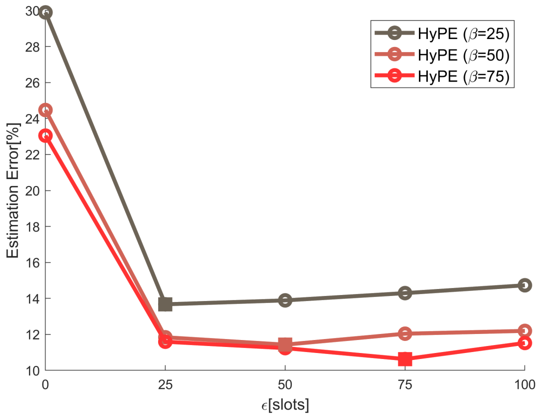


FIGURE 6. Estimation error of the proposed method according to ϵ.

against the increase in β. However, the estimation errors are still higher than those of other Bayesian-based estimation methods. The proposed HyPE method estimates with better accuracy even as β increases. Among these estimation methods, it achieves the lowest estimation errors of 10.12 [%] at $\beta = 75$ and 12.50 [%] at $\beta = 25$.

Figures 5 and 6 present the estimation errors of the proposed HyPE method against the maximum number of active UAVs (N_{max}) and pseudo-Bayesian update period (ϵ) in S-ALOHA-based tactical FANETs. Figure 5 corresponds to the outcomes of the proposed method with ϵ set to 50 and v_{th} set to 10 in a dynamic environment where α and β are configured as 5 and 50, respectively. It can be seen that the estimation error increases as N_{max} increases because it is more difficult to estimate an exact number against a wide estimation range. Specifically, the proposed method has estimation errors of 11.43 [%], 12.15 [%], 13.21 [%], 14.56 [%], 15.69 [%], and 16.90 [%] respectively as N_{max} increases by 10 from 50 to 100. These estimation errors can be mitigated by allocating resources with additional margins. However, for more efficient resource utilization, accurate estimation is crucial. Therefore, the proposed method accurately estimates the number of active UAVs to achieve efficient resource utilization.

In Figure 6, the proposed method with a fixed v_{th} of 10 was evaluated in a dynamic environment with α set to 5 and N_{max} set to 50. Here, the pseudo-Bayesian update period (ϵ) in the proposed method is varied between 0, 25, 50, 75, and 100, while the variation period (β) ranges from 25 to 75. The minimum estimation error in each environment is found when both ϵ and β have the same values. This is because the proposed method can be more effectively adapted to these changes by performing a pseudo-Bayesian update immediately at the time of traffic change. For example, in an environment with $\beta = 25$, the minimum estimation error is 13.67 [%] when using the proposed method with $\epsilon = 25$, and in an environment with $\beta = 75$, the estimation error is minimized to 10.63 [%] when ϵ is set to 75. In addition, it can also be seen that the estimation error increases as the two values are far away.

IV. CONCLUSION

This study proposes the HyPE method to estimate the number of active UAVs in S-ALOHA-based tactical FANETs. To adapt to the network traffic dynamics of FANETs, a hybrid approach that combines pure-Bayesian and pseudo-Bayesian estimation methods is devised. To evaluate the performance of the proposed method, the low-bound, Schoute, and max-probability methods were considered benchmark methods. In addition, to investigate the worst-case performance of the benchmark and proposed methods in tactical FANET environments, this paper demonstrated two additional results for $f(N, \hat{N})$ according to variation period and variation step size. Specifically, it was demonstrated that the proposed method had the best estimation accuracy and adaptability to the variations in the number of active UAVs. For example, the estimation errors were 8.61 [%] and 13.83 [%] when $\alpha = 0$ and $\alpha = 10$, respectively, and 10.12 [%] and 12.50 [%] when $\beta = 75$ and $\beta = 25$, respectively. In addition, simulations were conducted based on changes in factors such as the maximum number of active UAVs and pseudo-Bayesian update period to confirm the robustness of the proposed method. Specifically, the proposed method shows that the estimated error of 5.46 [%] increases when the maximum number of active UAVs increases from 50 to 100, and the lowest estimation error occurs when the pseudo-Bayesian update period is equal to the variation period, as well as the increase in the estimation error is not significant even when the two values do not match. The simulation results unequivocally demonstrate the superior performance of the proposed HyPE method. This method outperforms the benchmark methods and exhibits notable adaptability to the dynamic and frequent changes inherent to FANET environments. Through the proposed method, the computational complexity of pure-Bayesian calculations, which is challenging to implement on an onboard processor, and the lower estimation accuracy associated with the pseudo-Bayesian method are effectively resolved. Furthermore, this estimation method can be utilized to adjust not only the transmission probability of each

UAV but also the frame length, thereby improving network performance.

ACKNOWLEDGMENT

(Jimin Jeon and Junseung Lee contributed equally to this work.)

REFERENCES

[1] H. Lee, B. Lee, H. Yang, J. Kim, S. Kim, W. Shin, B. Shim, and H. V. Poor, "Towards 6G hyper-connectivity: Vision, challenges, and key enabling technologies," *J. Commun. Netw.*, vol. 25, no. 3, pp. 344–354, Jun. 2023.

[2] S. Gangopadhyay and V. K. Jain, "A position-based modified OLSR routing protocol for flying ad hoc networks," *IEEE Trans. Veh. Technol.*, vol. 72, no. 9, pp. 12087–12098, Sep. 2023, doi: 10.1109/TVT.2023.3265704.

[3] C. Wang, J. Zhao, X. Wu, W. Ma, H. Tian, Q. Yu, H. Shi, Y. Yao, and X. Hao, "Elastic routing mechanism for flying ad hoc network," *IEEE Access*, vol. 10, pp. 98712–98723, 2022.

[4] Y. Lee, J. Jeon, J. Choi, S. Park, B. C. Jung, and H. Lee, "P^2URE: Proactive and probabilistic uncovered neighbor-aware relay-selection method in multi-hop FANETs," *IEEE Access*, vol. 12, pp. 35097–35108, 2024.

[5] E. Kim, J. Kim, J.-H. Kim, and H. Lee, "HiMAQ: Hierarchical multi-agent Q-learning-based throughput and fairness improvement for UAV-aided IoT networks," *J. Netw. Comput. Appl.*, vol. 223, Mar. 2024, Art. no. 103813.

[6] J. Lee, S. Lee, S. H. Chae, and H. Lee, "Performance analysis of cooperative dynamic framed slotted-ALOHA with random transmit power control in A2G communication networks," *IEEE Access*, vol. 10, pp. 106699–106707, 2022.

[7] X. Qiu, Y. Yang, L. Xu, J. Yin, and Z. Liao, "Maintaining links in the highly dynamic FANET using deep reinforcement learning," *IEEE Trans. Veh. Technol.*, vol. 72, no. 3, pp. 2804–2818, Mar. 2023.

[8] Z. Wang, H. Yao, T. Mai, Z. Xiong, X. Wu, D. Wu, and S. Guo, "Learning to routing in UAV swarm network: A multi-agent reinforcement learning approach," *IEEE Trans. Veh. Technol.*, vol. 72, no. 5, pp. 6611–6624, May 2023.

[9] R. H. Jacobsen, L. Matlekovic, L. Shi, N. Malle, N. Ayoub, K. Hageman, S. Hansen, F. F. Nyboe, and E. Ebeid, "Design of an autonomous cooperative drone swarm for inspections of safety critical infrastructure," *Appl. Sci.*, vol. 13, no. 3, p. 1256, Jan. 2023.

[10] N. Norhashim, N. L. M. Kamal, S. A. Shah, Z. Sahwee, and A. I. A. Ruzani, "A review of unmanned aerial vehicle technology adoption for precision agriculture in Malaysia," *Unmanned Syst.*, vol. 1, pp. 1–19, Feb. 2023.

[11] A. Mehmood, Z. Iqbal, A. A. Shah, C. Maple, and J. Lloret, "An intelligent cluster-based communication system for multi-unmanned aerial vehicles for searching and rescuing," *Electronics*, vol. 12, no. 3, p. 607, Jan. 2023.

[12] S. Luo, Y. Liang, Z. Luo, G. Liang, C. Wang, and X. Wu, "Vision-guided object recognition and 6D pose estimation system based on deep neural network for unmanned aerial vehicles towards intelligent logistics," *Appl. Sci.*, vol. 13, no. 1, p. 115, Dec. 2022.

[13] B. Xu, K. Zhao, Q. Luo, G. Wu, and W. Pedrycz, "A GV-drone arc routing approach for urban traffic patrol by coordinating a ground vehicle and multiple drones," *Swarm Evol. Comput.*, vol. 77, Mar. 2023, Art. no. 101246.

[14] O. S. Oubbati, M. Mozaffari, N. Chaib, P. Lorenz, M. Atiquzzaman, and A. Jamalipour, "ECaDecad: Energy-efficient routing in flying ad hoc networks," *Int. J. Commun. Syst.*, vol. 32, no. 18, p. e4156, 2019.

[15] S. Lee, H. Yu, and H. Lee, "Multiagent Q-learning-based multi-UAV wireless networks for maximizing energy efficiency: Deployment and power control strategy design," *IEEE Internet Things J.*, vol. 9, no. 9, pp. 6434–6442, May 2022.

[16] S. Lim, H. Yu, and H. Lee, "Optimal tethered-UAV deployment in A2G communication networks: Multi-agent Q-learning approach," *IEEE Internet Things J.*, vol. 9, no. 19, pp. 18539–18549, Oct. 2022.

[17] G. M. Cappello, G. Colajanni, P. Daniele, L. Galluccio, C. Grasso, G. Schembra, and L. Scrimali, "Optimizing FANET lifetime for 5G softwarized network provisioning," *IEEE Trans. Netw. Service Manage.*, vol. 19, no. 4, pp. 4629–4649, Dec. 2022.

[18] G. Raja, S. Anbalagan, A. Ganapathisubramaniyan, M. S. Selvakumar, A. K. Bashir, and S. Mumtaz, "Efficient and secured swarm pattern multi-UAV communication," *IEEE Trans. Veh. Technol.*, vol. 70, no. 7, pp. 7050–7058, Jul. 2021.

[19] Y. Lu, W. Wen, K. K. Igorevich, P. Ren, H. Zhang, Y. Duan, H. Zhu, and P. Zhang, "UAV ad hoc network routing algorithms in space–air–ground integrated networks: Challenges and directions," *Drones*, vol. 7, no. 7, p. 448, Jul. 2023.

[20] Q. Usman, O. Chughtai, N. Nawaz, Z. Kaleem, K. A. Khaliq, and L. D. Nguyen, "Lifetime improvement through suitable next hop nodes using forwarding angle in FANET," in *Proc. 4th Int. Conf. Recent Adv. Signal Process., Telecommun. Comput. (SigTelCom)*, Aug. 2020, pp. 50–55.

[21] N. Mansoor, Md. I. Hossain, A. Rozario, M. Zareei, and A. R. Arreola, "A fresh look at routing protocols in unmanned aerial vehicular networks: A survey," *IEEE Access*, vol. 11, pp. 66289–66308, 2023.

[22] Q. Xue, Y. Yang, J. Yang, X. Tan, J. Sun, G. Li, and Y. Chen, "QEHLR: A Q-learning empowered highly dynamic and latency-aware routing algorithm for flying ad-hoc networks," *Drones*, vol. 7, no. 7, p. 459, Jul. 2023.

[23] H. Vogt, "Efficient object identification with passive RFID tags," in *Proc. Int. Conf. Pervasive Comput.*, 2002, pp. 98–113.

[24] F. Schoute, "Dynamic frame length Aloha," *IEEE Trans. Commun.*, vols. TC-31, no. 4, pp. 565–568, Apr. 1983.

[25] W.-T. Chen, "An accurate tag estimate method for improving the performance of an RFID anticollision algorithm based on dynamic frame length Aloha," *IEEE Trans. Autom. Sci. Eng.*, vol. 6, no. 1, pp. 9–15, Jan. 2009.

[26] J.-B. Eom and T.-J. Lee, "Accurate tag estimation for dynamic framed-slotted Aloha in RFID systems," *IEEE Commun. Lett.*, vol. 14, no. 1, pp. 60–62, Jan. 2010.

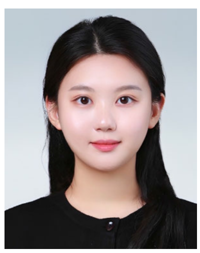
[27] Q. Tong, X. Zou, and H. Tong, "Dynamic framed slotted Aloha algorithm based on Bayesian estimation in RFID system," in *Proc. WRI World Congr. Comput. Sci. Inf. Eng.*, vol. 1, Mar. 2009, pp. 384–388.

[28] H. Wu and Y. Zeng, "Bayesian tag estimate and optimal frame length for anti-collision Aloha RFID system," *IEEE Trans. Autom. Sci. Eng.*, vol. 7, no. 4, pp. 963–969, Oct. 2010.

[29] R. Annur, W. Srichavengsup, S. Nakpeerayuth, and L. Wuttitsittikulkij, "Bayesian method of slotted Aloha based anti-collision protocol for RFID systems," in *Proc. IEEE 12th Int. Symp. Auto. Decentralized Syst.*, Mar. 2015, pp. 87–90.

[30] J. Liu, M. Qu, and H. Jin, "A simple Pseudo-Bayesian backoff algorithm for unsaturated slotted CSMA systems," in *Proc. IEEE 87th Veh. Technol. Conf. (VTC Spring)*, Jun. 2018, pp. 1–5.

[31] J. Liu and H. Jin, "Delayed Pseudo-Bayesian transmission control for S-ALOHA systems," in *Proc. Int. Conf. Inf. Commun. Technol. Converg. (ICTC)*, Oct. 2020, pp. 725–727.



JIMIN JEON (Student Member, IEEE) received the B.S. degree from the School of Electronic and Electrical Engineering, Hankyong National University, Anseong, South Korea, in 2023. She is currently pursuing the M.S. degree with the Department of AI Convergence Network, Ajou University, Suwon, South Korea.

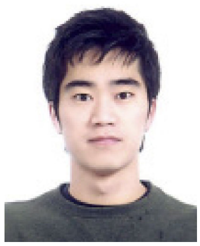
Her current research interests include B5G/6G wireless communication, UAV-aided communications, reinforcement learning-based wireless resource management, and the Internet of Things. She was a recipient of the Undergraduate Student Paper Award from Korean Institute of Communications and Information Sciences (KICS) Summer Conference, in 2022, and Korea Photonics Technology Institute (KOPTI) Best Paper Award from the KICS Winter Conference, in 2023.

JUNSEUNG LEE (Student Member, IEEE) received the B.S. and M.S. degrees from the School of Electronic and Electrical Engineering, Hankyong National University, Anseong, South Korea, in 2022 and 2024, respectively. His current research interests include B5G/6G wireless communications, ultra-dense distributed networks, reinforcement learning for UAV networks, unsupervised learning for wireless communication networks, and the Internet of Things.

TAEWOOK KIM (Student Member, IEEE) received the B.S. degree from the School of Electronic and Electrical Engineering, Hankyong National University, Anseong, South Korea, in 2024. He is currently pursuing the M.S. degree with the Department of AI Convergence Network, Ajou University, Suwon, South Korea. His current research interests include B5G/6G wireless communication, UAV-aided communications, reinforcement learning-based wireless resource management, and satellite networks.

JAEHA AHN received the B.S. and M.S. degrees from the Department of Electrical Engineering, Pohang University of Science and Technology (POSTECH), Pohang, South Korea, in 2014. He is currently pursuing the Ph.D. degree in electrical engineering with Korea Advanced Institute of Science and Technology (KAIST), Daejeon, South Korea. Since 2014, he has been a Senior Researcher with the Agency for Defense Development. His current research interests include mobile ad-hoc networks (MANETs), military tactical networks, and unmanned aerial vehicle (UAV) swarm networks.

YOUNGBIN YU received the B.S. degree in information industry engineering and the M.S. degree in computer science from Yonsei University, Seoul, South Korea, in 2005. In 2007, he was a Researcher with the Electronics Information and Communications Research Institute, Samsung. He is currently a Chief Research Engineer with the C4I Research and Development Center, LIG Nex1. His research interests include mobile ad-hoc networks (MANETs), military tactical networks, and unmanned aerial vehicle (UAV) swarm networks.



MIN LEE received the B.S. and Ph.D. degrees in electrical and computer engineering from Ajou University, Suwon, South Korea, in 2006 and 2014, respectively. Since 2014, he has been a Chief Research Engineer with the C4I Research and Development Center, LIG Nex1, Seongnam, South Korea. His research interests include cooperative communication technology in wireless networks, medium access control (MAC) protocol design in wireless ad-hoc networks, and wireless networking technology in unmanned aerial vehicle (UAV) swarm systems.

HEEJUNG YU (Senior Member, IEEE) received the B.S. degree in radio science and engineering from Korea University, Seoul, South Korea, in 1999, and the M.S. and Ph.D. degrees in electrical engineering from Korea Advanced Institute of Science and Technology (KAIST), Daejeon, South Korea, in 2001 and 2011, respectively. From 2001 to 2012, he was with the Electronics and Telecommunications Research Institute (ETRI), Daejeon. From 2012 to 2019, he was with Yeungnam University, South Korea. He is currently a Professor with the Department of Electronics and Information Engineering, Korea University, Sejong, South Korea. His research interests include statistical signal processing and communication theory.

HOWON LEE (Senior Member, IEEE) received the B.S., M.S., and Ph.D. degrees in electrical and computer engineering from 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/Team Leader of the Knowledge Convergence Team, KAIST Institute for Information Technology Convergence (KI-ITC). From 2012 to 2024, he was with the School of Electronic and Electrical Engineering and the Institute for IT Convergence (IITC), Hankyong National University (HKNU), Anseong, South Korea. He has also experienced as a Visiting Scholar with the University of California at San Diego (UCSD), La Jolla, CA, USA, in 2018. Since 2024, he has been with the Department of Electrical and Computer Engineering, Ajou University, Suwon, South Korea. 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 and satellite 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 a recipient of the Telecommunications Technology Association (TTA) Paper Contest Encouragement Award, in 2011, the Best Paper Award from the Korean Institute of Communications and Information Sciences (KICS) Summer Conference, in 2015, the Best Paper Award from the KICS Fall Conference, in 2015, the Honorable Achievement Award from 5G Forum Korea, in 2016, the Best Paper Award from the KICS Summer Conference, in 2017, the Best Paper Award from the KICS Winter Conference, in 2018, the Best Paper Award from the KICS Summer Conference, in 2018, the Best Paper Award from the KICS Winter Conference, in 2020, the Haedong Grand Prize from the KICS Summer Conference, in 2022, and the Haedong Grand Prize from the KICS Winter Conference, in 2023. He received the Minister's Commendation by the Minister of Science and ICT, in 2017.