EFTA: An Energy-efficient, Fault-Tolerant, and Area-optimized UAV Placement Scheme for Search Operations

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***Abstract*—Unmanned aerial vehicle (UAV) networks have widespread applications, ranging from surveillance and disaster management in the military domain to transportation and delivery of goods in the civilian domain. Regardless of the application, the placement of routing UAV nodes (especially in networks spanning long distances) is crucial in determining network performance parameters such as network lifetime and data transmission delay. In this paper, an *E*nergy-efficient, *F*ault-*T*olerant, and *A*rea-optimized UAV placement scheme (EFTA) is proposed for search operations. A cluster-based UAV network is considered, in which the Cluster Members (CMs) are mobile and scan the geographic area of interest. The Cluster Heads (CHs) are quasi-static and route information from the CMs to the Ground Control Station (GCS). A multi-objective Cuckoo Search Algorithm is used to determine the placement of the CHs while minimizing energy consumption, maximizing area coverage, and maximizing tolerance to node failures. Further, a comprehensive analysis was performed against a state-of-the-art UAV placement algorithm. The analysis showed that EFTA gives a significant performance improvement when compared to the competing placement scheme in fault tolerance, power consumption, network lifetime, end-to-end delay, and packet delivery ratio.**

***Index Terms*—UAVs, search and rescue, optimization, cuckoo search, UAV placement**

I. Introduction

Unmanned Aerial Vehicles (UAVs) have become increasingly popular due to their versatility and reduced human intervention, especially in dangerous situations. They have been used in a variety of fields, such as agriculture, military, forest monitoring, and disaster management operations. Based on the application, the system may be a single UAV system or a multi-UAV system. Multi-UAV networks increase the autonomy, reliability, and speed of the mission while reducing the communication requirements. In the event of a node failure in a multi-UAV system, the network reorganizes itself and maintains communication through other nodes, which is not possible in a single UAV system.

One of the most important applications of multi-UAV systems is search operations. These operations involve the scanning of a widespread region to get information about it, and are typically used in reconnaissance, surveillance or disaster management applications. These systems may also assess damage and relay this information to the concerned authorities. Most work on UAV placement is related to base station placement, where the area of interest is known beforehand, as can be seen in [1]. However, limited literature is available for search operations where the area of interest is not known.

A. Challenges

For search operations, the UAV node placement problem has multiple challenges:

1) Search operations require systems that can assess an area and relay this information to the concerned authorities. While their mobility and size may be attractive for such operations, UAVs have limited power resources and operating time. Hence, conserving the energy of individual nodes in a network and using it efficiently is essential in search operations.
2) Such systems must cover as much area as possible, especially in sensitive operations such as disaster management or anomaly detection in reconnaissance missions. Therefore, UAV nodes must be placed such that they cover maximum area in minimum possible time.
3) In such time-sensitive applications, time lost due to node failure(s) can be catastrophic. Therefore, UAV networks used for such missions must provide alternate data transmission routes to their nodes to minimize data loss due to node failure(s).

B. Contributions

Keeping in mind the above considerations, an Energy-efficient, Fault-Tolerant, and Area optimized (EFTA) UAV placement scheme is proposed in this work. It is evaluated and compared to a state-of-the-art energy-efficient maximal coverage algorithm [2].

The main contributions of this work are as follows:

1) A novel metric ($\mathcal{FTI}$) is introduced to measure the tolerance of a UAV network to individual node failures

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2) A system model designed specifically to tackle search operations
3) A novel placement scheme - EFTA, for routing data among the UAV CHs that minimizes energy consumption, maximizes area covered, and is tolerant to node failures.
4) Intensive simulation studies which show that EFTA outperforms a state-of-the-art energy-efficient maximal coverage algorithm [2] in terms of energy efficiency, fault tolerance, network lifetime, end-to-end delay and packet delivery ratio.

It is to be noted here that the optimization problems of maximizing area and fault tolerance while minimizing power consumption are conflicting and NP-hard. Thus, a meta-heuristic algorithm, MOCS [3], is used to arrive at a solution. Moreover, as natural processes inspire meta-heuristics, they provide quality solutions that can be used in real-time scenarios and apply to different use cases, as shown in [4].

The rest of this article is organized as follows. Section II gives a brief overview of related works, followed by Section III, which gives a background of the considered system model. Section IV explains the proposed scheme for UAV placement. Section V discusses the results of simulations carried out, followed by the conclusion in Section VI.

II. Related Works

The placement of UAVs in a network is of prime importance as it determines its performance in terms of network lifetime, energy usage, and delay in data transmission. Further, the placement of UAVs may be fixed or dynamic. An important UAV application where placement plays an important role is provision of cellular services using UAV base stations. In [1], Arani *et al.* proposed a novel learning-based mechanism for the three-dimensional deployment of UAVs to assist terrestrial networks. Low complexity algorithms based on the multi-armed bandit and satisfaction methods were used to learn UAVs' locations along with tools from reinforcement learning to arrive at the optimum placement. Another method proposed for base station placement is [5], where a density-aware placement algorithm was used to maximize the number of users covered subject to the constraint of the minimum required data rates per user. In [2], Alzenad *et al.* considered a 3-D placement algorithm that provided energy-efficient maximal coverage. The UAV mounted base station deployment in the horizontal dimension was first modeled as a circle placement problem and then a smallest enclosing circle problem.

In [6], UAV swarm positions were optimized to achieve a high multiplexing gain in line-of-sight MIMO backhaul. The authors developed two distributed algorithms for this - one based on gradient descent and another that used brute force. Both of these algorithms showed better performance as opposed to random swarm placement. Pan *et al.* [7] investigated a utility maximization problem for UAV placement and resource allocation in a software-defined network. The proposed solution used alternating maximization iterative algorithm, a successive convex optimization technique, and the modified alternating direction method of multipliers at different stages. Better results were obtained when bench-marked against other schemes at the cost of increased complexity.

However, this is not the only application that is dependent on UAV placement. In [8], a placement optimization problem was formulated to minimize the number of UAVs in the wind farm along with a routing optimization problem to minimize the inspection time. Both problems were NP-hard and solved using heuristics designed by the author. Zhang *et al.* [9] proposed a max-min energy harvesting problem by optimizing the UAVs' placement based on a non-linear energy harvesting model for wireless power transfer applications. The problem was solved by using the bat algorithm and ant colony optimization algorithm. For search operations, no placement schemes exist in literature, to the best of the authors' knowledge.

III. System Model

A. Nodes in Network

This work considers a UAV network with the following nodes:

1) Ground Control Station (GCS):: The GCS acts as a data sink for the network and has no power constraints. The remaining nodes direct all relevant information, such as the number and location of survivors, to the GCS. Further rescue-related actions are taken here as well.

2) Cluster Heads (CHs):: These are the UAVs with low mobility, enhanced computational power for complex data processing, and enhanced energy characteristics. EFTA is used to place these CHs. Once the CHs are placed, they remain *quasi-static*. Their primary purpose is to act as routers for information from the CMs to the GCS.

3) Cluster Members (CMs):: These are highly mobile UAVs with minimal computational abilities. Their main task is to search the area allotted to them and send any necessary information (such as detection of a survivor) to a CH, which then routes this information to the GCS.

B. Network Layout

A rectangular search area is considered in this work, and the nodes are depicted in Fig. 1. The GCS (denoted by a tower with dark blue background) is located at one corner of the search area, whereas both the CHs and CMs are distributed throughout the search area. The CHs (denoted by the UAVs with a light blue background) are quasi-static and act as routers for the CMs.

C. Flow of Information

CMs are responsible for scanning a designated area. On identifying objects of interest in that area, they forward their location to the nearest CH. Using a multi-hop routing algorithm, the CH subsequently forwards this information to the GCS.

IV. EFTA: UAV Placement Scheme

The objective of EFTA is to place CHs such that the area covered and fault tolerance are maximized while minimizing the power consumption. MOCS is used for solving

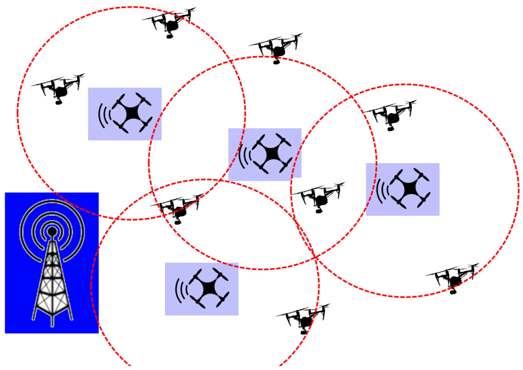

Fig. 1: Network Layout

these constraints simultaneously and providing a solution. The following subsections explain the constituent optimization problems:

A. Maximizing Area Coverage

The rectangular area to be covered is modeled as a grid consisting of cells of dimensions $100m \times 100m$. Thus, the area covered by the CHs is proportional to the number of cells covered by them, and the objective is to maximize the total number of grid cells covered by the CHs.

Let the network consist of k CHs, whose positions are denoted by (x_D^t, y_D^t), where $t = \{1, 2, 3, 4...., k\}$. Further, consider a binary variable $u[i][j] \in \{0,\ 1\}$ such that $u[i][j] = 1$, if and only if the cell with coordinates (i, j) in the grid is covered by a CH. A CH covers a cell (i, j) in the grid only if the distance of the CH from the cell is less than the transmission range R_0. A CH covers a cell if the below condition is satisfied for a cell with coordinates (i, j) in the grid:

$$(x_D^t - i)^2 + (y_D^t - j)^2 \leq R_0^2, \tag{1}$$

where R_0 is the transmission range of a CH. In this work, an area is represented by a grid G consisting of $m \times n$ cells, each of which are represented by a binary variable $u[i][j]$ as defined above.

The area maximization problem can thus be defined as follows:

$$\begin{aligned} & \textit{maximize} \sum_{i=1}^{m} \sum_{j=1}^{n} u[i][j] \\ & \textit{such that} \\ & u[i][j] = 1 \textit{ iff} \\ & (x_D^t - i)^2 + (y_D^t - j)^2 \leq R_0^2 \\ & \textit{for any } t \ \epsilon \ \{1, 2, 3...k\} \end{aligned} \tag{2}$$

Thus, to maximize the area covered by the CHs, the number of grid cells covered by the CHs is maximized.

B. Minimizing Nodal Power Consumption

The CH power consumption model used in this work is based on [10], where the power consumed is modeled as a function of the power consumed in transmitting and receiving a signal from one node to another. The following equation is used to model the energy lost, E(q), in the one transmission:

$$E(q) = (q-1)E_{R0} + q\,E_{T0} + \frac{\eta}{\gamma} \sum_{l=1}^{q} d_l^{\alpha}, \tag{3}$$

where E_{T0} and E_{R0} are constants representing distance-independent terms for transmitting and receiving power respectively for one hop, γ is the efficiency of the radio's power amplifier, η is the power consumed by the power amplifier at maximum efficiency, α is the shadowing/fading effect constant, q is the number of hops associated with the transmission, and d_l is the distance associated with the lth hop in the transmission. Hence, in this work, the energy constraint is modeled as the average power lost in sending information from a CH in the network to the GCS. In case a CH requires multi-hop routing to send data to the GCS, the total power lost in transmitting data is calculated with respect to the shortest distance path available to the CH. Note that distance here refers to the distance a packet has to travel to reach the GCS from a CH.

Let k CHs be present at various cells and consider two matrices N and D of sizes $k \times 1$ and $k \times k$ respectively. N contains the number of hops required for each CH to send data to the GCS, while D contains the distance associated with each hop from a given CH to the GCS. Since the maximum number of hops while transmitting a packet from a CH to the GCS is k hops, the size of D is $k \times k$. For example, D_{ij} is the distance of the jth hop in a transmission from the ith CH to the GCS. Thus, from Eq. (3) nodal power consumption ($\mathcal{NPC}$) is defined as follows: Thus, this work defines nodal power consumption ($\mathcal{NPC}$) as follows:

$$\mathcal{NPC} = \frac{\sum_{j=1}^{k} \left((N_j - 1)E_{R0} + N_j E_{T0} + \frac{\eta}{\gamma} \sum_{i=1}^{N_j} D_{ij}^{\alpha}\right)}{k}, \tag{4}$$

where N_j is the jth element of matrix N, E_{T0} and E_{R0} are constants representing distance-independent terms for transmitting and receiving power respectively for one hop, γ is the efficiency of the radio's power amplifier, η is the power consumed by the power amplifier at maximum efficiency and α is the shadowing/fading effect constant.

Thus, this work aims to minimize the power consumed in data transmission from any CH to the GCS by minimizing $\mathcal{NPC}$.

C. Maximizing Fault Tolerance Index ($\mathcal{FTI}$)

The third objective takes into account the ability of the network to tolerate node failures. Fault tolerance is of prime importance as it is essential to ensure that this UAV network is robust to the failure of one or more UAV nodes. As a measure of fault tolerance, a novel index is introduced by this work - the Fault Tolerance Index ($\mathcal{FTI}$). $\mathcal{FTI}$ is defined as the average number of connections of CHs with their neighbors in the network. A greater number of average connections ($\mathcal{FTI}$) would allow the network to use the nodes' energies more evenly and, therefore, result in a higher network lifetime. Further, a high $\mathcal{FTI}$ would provide CHs with alternate routes to send information if one or more nodes fail. Therefore, the dependence of the network on individual nodes reduces, thereby increasing the robustness of the network to node failures.

Consider a UAV network with k CHs present at various cells, whose positions are denoted by $\{x_D^t, y_D^t\}$, $t \,\epsilon$ {1,2,3,4....,k}. Consider a connections matrix C of size $k \times k$ defined such that $C[i][j] = 1$ if nodes i and j are within distance R_0 (transmission range of CHs) of one another

$$(x_D^i - x_D^j)^2 + (y_D^i - y_D^j)^2 \leq R_0^2, \tag{5}$$

and $C[i][j] = 0$ if the above inequality is not satisfied.
The mathematical representation of $\mathcal{FTI}$ is thus given as:

$$\mathcal{FTI} = \frac{\sum_{i=1}^{k} \sum_{j=1}^{k} C[i][j]}{k} \tag{6}$$

D. Problem Formulation

Let the UAV network consist of k CHs. Variables have meanings as defined in the previous subsections. Note that the default values of $C[i][j]$ and $u[i][j]$ are 0. Hence, the overall multi-objective optimization problem can be represented as below:

$$\textit{Maximize } \{ \sum_{i=1}^{m} \sum_{j=1}^{n} u[i][j] \ , \ \frac{\sum_{i=1}^{k} \sum_{j=1}^{k} C[i][j]}{k} \}$$

$$\&$$

$$\textit{Minimize } \{ \frac{\sum_{j=1}^{k} ((N_j - 1)E_{R0} \ + \ N_j E_{T0} \ + \ \frac{\eta}{\gamma} \sum_{i=1}^{N_j} D_{ij}^{\alpha})}{k} \}$$

such that

1. $N_i > 0$ *and* $N_i \leq k \ \forall \ i \ \epsilon \ \{1, 2, 3....k\}$
2. *C[i][j] = 1*
   if $(x_D^i - x_D^j)^2 + (y_D^i - y_D^j)^2 < R_0^2$ *for i,j* $\epsilon \ \{1, 2, 3....k\}$
3. *u[i][j] = 1*
   iff $(x_D^t - i)^2 + (y_D^t - j)^2 < R_0^2$ *for any* $t \ \epsilon \ \{1, 2, 3...k\}$

(7)

E. Multi-objective Cuckoo Search (MOCS) and NSGA-II

Cuckoo Search Algorithm [11] is a meta-heuristic algorithm based on the breeding behavior of certain species of cuckoos. The reason for choosing a meta-heuristic algorithm for EFTA is simple - multiple conflicting objectives have to be achieved, and the optimization problem is *NP hard*. There will be trade-offs, for example, between power consumption and the area covered. Moreover, the non-linearity of the constraints further makes it difficult to use deterministic algorithms over stochastic ones. On the other hand, the fast computation and the global nature of meta-heuristics make them a good choice for such a problem.

The algorithm incorporates the breeding behavior and the characteristics of Lévy flights, which brings a degree of randomness to the algorithm. Exploration and exploitation are two key characteristics of meta-heuristics. Exploration ensures diversity of solutions globally, while exploitation focuses on the current region where a good solution has been located to find an even better one. Lévy flights are used for both these characteristics - smaller steps from the current best solution would relate to exploitation, whereas larger steps relate to exploration or diversification [11]. For multiple objectives, the last step of breeding behavior is modified and can be found in [3]. It must be noted that MOCS does not use a weighted function. Instead, it optimizes the three constraints simultaneously to present a set of solutions. This is done by incorporating NSGA-II [12], an evolutionary genetic algorithm to compare and rank solutions using non-dominated sorting.

A characteristic of multi-objective optimization problems is that there exist multiple optimal solutions that form the Pareto front, which is a group of non-dominated solutions. While there are no practical approaches for obtaining a Pareto front, Lévy flights are also used to approximately generate it [13]. Lévy flights are incorporated when generating new solutions. For cuckoo i, the new solution generated for the $(r+1)$th iteration is given as:

$$s_i^{r+1} = s_i^r + \beta \oplus Levy(\lambda) \tag{8}$$

where β >0 is the step size and is decided based on the scope of the problem. Also, s_i is the *i*th solution, which corresponds to a $2k \times 1$ matrix containing the x and y coordinates of k CHs.

Hence, using MOCS and NSGA-II, the Pareto front is generated.

As a Pareto front generates a group of solutions, the following steps are carried out to choose the best solution out of them:

1) In search missions, the primary goal of UAVs is to search the area as exhaustively and as quickly as possible. To accomplish this, CMs must have at least 1 CH in communication range at all times. Therefore, the CHs must cover a minimum threshold of the area in the network. Hence, all solutions in the pareto front that cover less than 99% of the prescribed grid area are removed.
2) The remaining solutions are then ranked using the function below: (the three parameters have equal weightage)
$$f = NormFTI_i + NormArea_i - NormNPC_i \tag{9}$$
3) EFTA then chooses the solution with the highest value of f as its final output.

V. Performance Evaluation

This section presents a comprehensive comparative analysis between EFTA and Alzenad *et al.* [2]. As mentioned earlier, to the best of the authors' knowledge, no UAV placement schemes specifically addressing search operations exist in literature. Alzenad *et al.* [2] proposed a state-of-the-art, maximal coverage, energy-efficient UAV placement scheme for generic scenarios in applications using base-stations. As both [2] and EFTA aim at energy-efficient maximal coverage, this work uses [2] for performance comparison. This section is organized

TABLE I: Simulation Parameters

Parameter	Value
E_{R0}	0.1 mW
E_{T0}	0.1 mW
γ	0.3
α	2 (assuming free space)
η	5 $\times 10^5$
R_0	50 cells

as follows. Section V-A gives an overview of the simulation environment while section V-B displays results for the three metrics explained in Section IV - area coverage, $\mathcal{FTI}$ and $\mathcal{NPC}$. Section V-C presents a comparative analysis of network performance of EFTA and Alzenad *et al.* for $k = 6$.

A. Simulation Environment

For simulations, a rectangular search area is modeled as a grid of cells, each of size $100m \times 100m$. Further, a matrix X of size $k \times 2$ was defined to store the coordinates of the CHs within the grid. This matrix contains solutions obtained from MOCS. The optimization metrics for individual solutions were calculated using X. Note that all simulations were performed using MATLAB 2020b. The simulation parameters used by this work are as follows - E_{T0} = 0.1 mW, E_{R0} = 0.1 mW, γ = 0.3, α = 2 (assuming free space), η = 5 $\times 10^5$ and R_0 = 50 cells.

B. Placement Results

Figure 2 shows the Pareto Front generated for k=7. As mentioned above, function f defined in Eq. (9) is then used on the solutions in the Pareto Front to find a single optimal solution for the optimisation problem defined in Eq. (7).

EFTA was compared with [2] for 3 parameters : $\mathcal{FTI}$, $\mathcal{NPC}$, and Area Coverage. The simulations were run for $k = 4, 5, 6$ and 7 and the results are shown in Fig. 3, Fig. 4 and Fig. 5. Different dimensions of search area were chosen - $9km \times 9km$ for $k = 4$, $10km \times 10km$ for $k = 5$ and $12km \times 12km$ for $k = 6$ and 7. It may be noted that the area coverage for EFTA is comparable to [2], with a difference of under 0.5% in each case. The reason for [2] showing slightly better area coverage is that [2] aims to maximize area while ensuring energy efficiency. In other words, [2] maximises area first and then chooses the solution with best energy efficiency

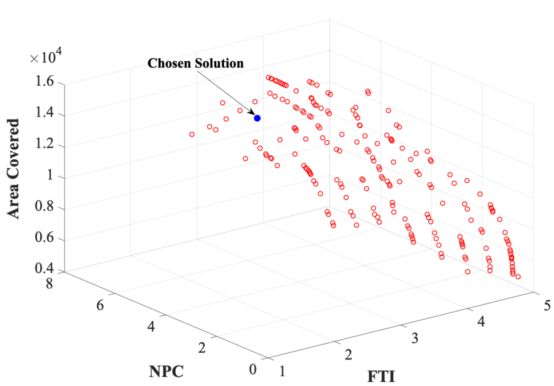

Fig. 2: Pareto Front for k=7

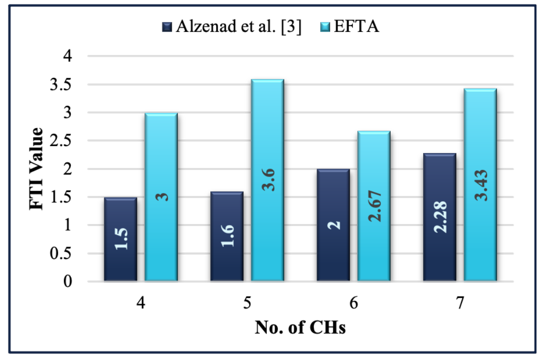

Fig. 3: Fault Toleratance Index ($\mathcal{FTI}$) Comparison

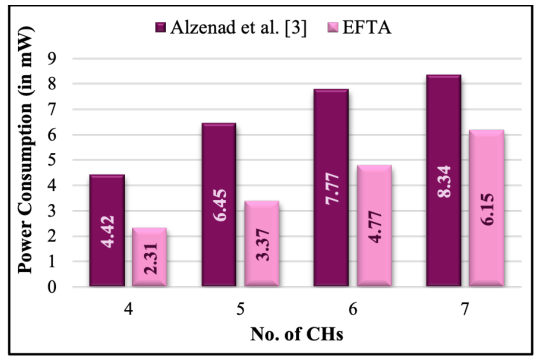

Fig. 4: Nodal Power Consumption ($\mathcal{NPC}$) Comparison

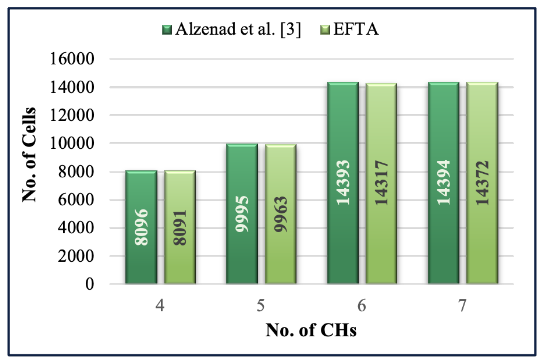

Fig. 5: Area Coverage Comparison

amongst those that cover the maximum area. Meanwhile, EFTA considers two more constraints while generating the pareto front - fault tolerance and power consumption in addition to the area covered. Hence, EFTA consistently shows higher $\mathcal{FTI}$ values indicating the existence of a greater number of alternate paths per node. Even in terms of $\mathcal{NPC}$, EFTA shows better performance by 40% on average.

C. Network Evaluation

For the purpose of network evaluation, placements obtained by EFTA and [2] for $k = 6$ were considered, and Optimized Link State Routing (OLSR) [14] was chosen as the routing protocol to compare metrics such as network lifetime, end-to-end delay, and Packet Delivery Ratio (PDR). It must be noted that network lifetime is the packet number until which all the CHs in the network were active. In these simulations, 2000

TABLE II: Comparative Analysis for $k = 6$

Parameter	Alzenad et al. [2]	EFTA
Network Lifetime (No. of packets)	1014	1732
End-to-end Delay	$6.004 \times 10^{-5}s$	$4.058 \times 10^{-5}s$
Packet Delivery Ratio (PDR)	0.495	0.859

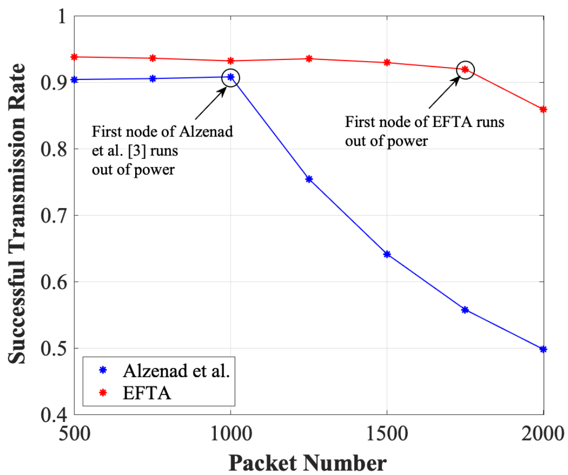

Fig. 6: Cumulative Packet Delivery Ratio (PDR) after every 250 packets

packets were collected and sent to the GCS from randomly chosen CMs. These CMs were chosen with the help of a normal distribution with zero mean and unit variance. The results have been presented in Table II.

As can be seen in Table II, EFTA performs significantly better than [2]. EFTA increases network lifetime by almost 71% and reduces the end-to-end delay for packet transmission by 33%. It also shows a considerable improvement of 73.5% in PDR. These findings can be attributed to the fact that EFTA provides not only good area coverage but also lower power consumption and a greater number of alternative routes. EFTA thus ensures the successful transmission of a greater number of packets to the GCS while simultaneously ensuring that individual CHs are not drained of their power.

The cumulative PDR trend for every 250 packets can be seen in Fig. 6. Clearly, as the first node of [2] ran out of power, the PDR dropped sharply. This sharp dip is highly undesirable for time-sensitive applications such as search operations. EFTA, on the other hand, maintains a consistent PDR for the first 1500 packets due to a higher network lifetime. Further, it shows a less steep drop in PDR when a node runs out of energy at 1732 packets. This less steep drop is attributed to the fact that EFTA shows higher $\mathcal{FTI}$ which results in the availability of a higher number of alternate paths for routing data in the network and hence, a greater robustness to node failures.

VI. Conclusions and Future Work

This paper presents EFTA, a novel multi-objective UAV placement scheme focused on search operations. Intensive simulations show that EFTA yields better fault tolerance and power consumption results while giving similar area coverage compared to a state-of-the-art placement scheme for UAV networks. Furthermore, EFTA also shows significant improvement in network performance in terms of network lifetime, delay, and packet delivery ratio. In future works, the focus will be to develop a novel routing scheme that incorporates EFTA to present an end-to-end solution for search operations.

VII. Acknowledgement

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