OPEN ACCESS
The Journal of Engineering and Exact Sciences – jCEC, Vol. 10 N. 07 (2024)
journal homepage: https://periodicos.ufv.br/jcec
eISSN: 2527-1075
ISSN: 2446-9416

An efficient Protocol for Enhanced Flynet Communication in Presence of Partitioning

Article Info:
Article history: Received 2024-09-09 / Accepted 2024-10-27 / Available online 2024-10-27
doi: 10.18540/jcecvl10iss7pp20064

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Abstract
This paper presents an adaptive fault-tolerant resource allocation protocol tailored for FlyNet, a dynamic aerial network characterized by its mobility and three-dimensional operational space. Addressing the challenges of network partitioning and resource allocation in aerial networks, the proposed algorithm dynamically adjusts to the network's changing topology, ensuring consistent and efficient resource management. Through robust fault tolerance mechanisms, the protocol enhances FlyNet's reliability, maintaining seamless communication and optimal resource utilization even amid node mobility and disruptions. Simulation results demonstrate the algorithm's effectiveness in adapting to dynamic environments, maximizing resource utilization, and minimizing communication delays.
Keywords: FlyNet. Fault-tolerant resource allocation. Dynamic air-to-air communication. Partitioning challenges. Uninterrupted operation.

1. Introduction

The emergence of flying ad hoc networks (FANs), exemplified by FlyNet, revolutionizes network dynamics by introducing mobile aerial nodes and unparalleled three-dimensional mobility (Bilen *et al*., 2022). This transformative architecture presents unique challenges and opportunities, demanding novel resource sharing algorithms specifically designed for aerial communication. FlyNet's dynamic nature, characterized by node mobility, varying altitudes, and fluctuating speeds, necessitates sophisticated resource sharing mechanisms that can adapt to these ever-changing conditions (Shayea *et al*., 2022). Effective resource allocation and coordination are paramount for optimizing network performance, ensuring reliability, and enabling seamless communication amidst airspace partitions, intermittent connections, and unpredictable movements.

This research addresses these challenges by proposing an enhanced fault-tolerant algorithm tailored for FlyNet. The algorithm specifically focuses on mitigating the impact of airspace partitions and improving resource utilization efficiency (Amer *et al*., 2020). By considering node mobility patterns, airspace partitioning phenomena, and communication disruptions unique to FlyNet, this study refines the algorithm to meet the evolving demands of aerial communication networks. Through a comprehensive exploration of resource allocation strategies, fault tolerance mechanisms, and performance optimization techniques customized for the aerial domain, this research strives to unlock new frontiers in network efficiency, resilience, and scalability within FlyNet's dynamic and spatially diverse environment (Tun *et al*., 2020).

Our vision is a future where seamless aerial connectivity and efficient resource management converge to redefine the boundaries of modern communication systems. By embracing the challenges and opportunities presented by FlyNet, we aim to propel the evolution of communication technologies, fostering a future where aerial networks seamlessly integrate into our interconnected world, ushering in a new era of airborne connectivity and communication excellence (Safari *et al*., 2022).

The structure of the paper unfolds as follows: Section 2 delves into the intricacies of airspace partitioning in FlyNet, elucidating the challenges posed and exploring key methodologies for partition detection. Moving forward, Section 3 offers a comprehensive examination of resource sharing dynamics tailored for the unique characteristics of FlyNet networks. Sections 4, 5, and 6 sequentially present an in-depth analysis of the original algorithm, its enhancements, and the novel functionalities proposed for optimized resource allocation in FlyNet environments. In Section 7, the simulation framework is outlined, accompanied by a detailed discussion of the simulation outcomes. Finally, Section 8 encapsulates the paper with conclusive remarks and future perspectives for advancing resource sharing algorithms in the dynamic realm of FlyNet networks.

2. The partition problem in flynet

Addressing the airspace partitioning problem is crucial for ensuring the robustness and reliability of communication within FlyNet, a pioneering example of flying ad hoc networks (FANs) that operate in dynamic aerial environments. Unlike traditional terrestrial networks, FlyNets leverage mobile aerial nodes, such as drones, to establish a versatile network infrastructure across three-dimensional airspace. This innovative approach opens up numerous applications in fields like environmental monitoring, disaster response, and remote communication, where the agility and flexibility of aerial nodes provide significant advantages (Alsabah *et al*., 2021; Lakew *et al*., 2020).

However, the unique characteristics of FlyNet also introduce challenges, prominently among them being the airspace-partitioning problem. Airspace partitioning occurs when physical obstacles, regulatory restrictions, or network congestion create divisions within the operational airspace, hindering communication between nodes. These divisions can arise due to various factors:

- **Physical Obstacles**: Natural features such as mountains, buildings, or other physical barriers can attenuate communication signals, effectively segmenting the airspace into isolated pockets where nodes cannot communicate effectively Mohamed (2020).
- **Regulatory Restrictions**: Airspace regulations impose designated zones for manned aviation, restricted areas, or no-fly zones. Compliance with these regulations is crucial for safety but can lead to fragmented airspace and network segmentation if FlyNet nodes are unable to operate in certain areas (Chaurasia and Mohindru, 2021).
- **Network Congestion**: In densely populated areas of FlyNet, where numerous nodes are active, airspace congestion can occur. To manage this, network management protocols may temporarily partition the airspace into smaller sub-networks to alleviate congestion and maintain overall network stability (Gupta *et al*., 2021).

The consequences of airspace partitioning are significant and can severely impact FlyNet's operational effectiveness, for example, when airspace divisions occur, nodes within the same network segment may possess critical resources (such as data, processing power, or sensor capabilities) that are inaccessible to nodes in other segments due to communication blackout. This restricts the efficient sharing of resources and collaboration among nodes, diminishing overall network efficiency (Chen *et al*., 2020; Wang *et al*., 2020). In addition, established communication paths between nodes may be disrupted when partitions occur, leading to increased latency, packet loss, and instability in data transmission. This disruption is particularly problematic in time-sensitive applications such as disaster response or real-time environmental monitoring, where uninterrupted data exchange is essential (Abdulhae *et al*., 2022).

To address these challenges effectively, researchers are developing innovative solutions tailored to FlyNet's unique operational environment such as:

- **Dynamic Resource Allocation Algorithms**: Advanced algorithms can dynamically adjust resource allocation strategies in response to airspace partitions. By rerouting resources from unreachable nodes to those within accessible segments, these algorithms optimize resource utilization and mitigate the performance degradation caused by airspace divisions.
- **Enhanced Fault Tolerance Mechanisms**: Robust fault tolerance mechanisms are essential for maintaining communication continuity despite temporary disruptions caused by airspace partitions. Techniques such as buffer overflow management, error correction codes, or adaptive routing algorithms can ensure alternative communication paths are swiftly activated when primary paths are obstructed (Ramamoorthy and Thangavelu, 2022).
- **Network Partition Awareness and Reconfiguration Protocols**: Sophisticated protocols enable FlyNet to detect airspace partitions and autonomously reconfigure its network topology. This adaptive capability allows FlyNet to temporarily partition into smaller sub-networks during disruptions and seamlessly reintegrate once connectivity is restored, ensuring continuous and reliable communication (Abdulhae *et al*., 2022).

Efforts in these areas are pivotal for overcoming the complexities of airspace partitioning within FlyNet and enhancing its capability to deliver resilient and efficient communication services across diverse operational scenarios. By addressing these challenges head-on, researchers aim to unlock FlyNet's full potential as a transformative technology in modern communication systems, where seamless aerial connectivity and adaptive resource management redefine the possibilities of networked aerial platforms.

3. Related works

This section provides a summary of the key developments in dynamic resource allocation strategies that took place for FlyNets from 2019 to 2024. Methods that were used classify these works into clustering-based, game-theory-based, machine learning-based, and others.

3.1 Clustering-Based Allocation

We find many studies in this allocation method:

- **Dynamic Cluster Formation for Resource Sharing in FlyNets** : In the study of (Gholami and Brennan, 2022), a dynamic cluster formation algorithm that adapts to real-time drone mobility and channel conditions is introduced. It allows clusters to adjust to network changes, improving resource sharing and communication within these clusters. By evaluating mobility patterns and channel quality, the algorithm forms clusters that adapt to changes, optimizing resource allocation within each group. Simulations indicate enhanced resource utilization and communication efficiency when compared to static clustering methods.
- **Maintaining Connectivity in Mobile Drone Clusters for Efficient Resource Allocation** (Nouri *et al*., 2021): This work addresses the challenge of maintaining stable communication within mobile drone clusters, essential for effective resource allocation. By incorporating predictive models that anticipate drone movements, the system adjusts clusters proactively to ensure reliable links. The results show enhanced connectivity and resource distribution, particularly in highly dynamic environments.
- **Scalable Resource Allocation in FlyNets Using Distributed Clustering:** The paper of (More and Hall, 2004) proposes a distributed clustering method for scalable resource allocation in large-scale FlyNets. By allowing drones to exchange local information to form clusters, this approach reduces the communication overhead typically associated with

centralized methods. The decentralized nature enhances robustness and scalability, achieving lower latency than traditional centralized techniques.

- **Energy-Efficient Cluster-Based Resource Allocation for FlyNet UAVs with Mobility Prediction (**Du *et al.* ,2018)**:** Focusing on energy efficiency, this paper presents a cluster-based resource allocation scheme that includes mobility prediction to reduce unnecessary transmissions. By predicting drone movements, the scheme forms energy-efficient clusters that minimize communication. The experimental results show significant operational time extensions for drones through reduced energy expenditure.

3.2 Game Theory-Based Allocation

- **Fair and Efficient Resource Allocation in FlyNets Using Coalition Game Theory**: The paper of (Xu and Yu, 2014) utilizes coalition game theory to achieve fair and efficient resource allocation. Drones form coalitions to share resources equitably, minimizing conflicts and enhancing network performance. The cooperative approach ensures that resources are allocated in a fair and efficient manner, validated through analytical and simulation results.
- **A Stackelberg Game Approach for Resource Allocation in FlyNets with Quality-of-Service Guarantees**: Utilizing a Stackelberg game model, this work designates a central entity as the leader and drones as followers. The leader guarantees Quality of Service (QoS) for critical applications while optimizing resource allocation. The results show that this framework effectively improves QoS adherence and resource efficiency (Rathi et al., 2022).
- **Incentive-Compatible Resource Allocation in FlyNets Using Auction Mechanisms**: This study explores auction mechanisms for resource allocation, encouraging drones to truthfully report their resource needs, leading to efficient allocation. Various auction models are presented and evaluated, showing high efficiency and incentive compatibility in resource distribution (Xi *et al*., 2023).
- **Dynamic Coalition Formation for Spectrum Sharing in FlyNets Using Game Theory**: This research focuses on spectrum sharing using game theory, allowing drones to form coalitions based on spectrum availability and communication needs. The dynamic coalition formation algorithm optimizes spectrum utilization, ensuring necessary resources for effective communication, as validated by simulation results (Khan *et al*., 2010).

3.3 Machine Learning-Based Allocation

- **Deep Learning for Proactive Resource Allocation in Mobile Aerial Networks** (Liang *et al*., 2019): This paper leverages deep learning models trained on historical drone data to predict future movements and resource demands. The proactive allocation strategy uses these predictions to pre-allocate resources, reducing latency and improving overall network efficiency. The study demonstrates significant enhancements in resource allocation accuracy.
- **Machine Learning-Based Resource Allocation for Delay-Sensitive Applications in FlyNets**: This work introduces a machine learning-based allocation scheme prioritizing delay-sensitive applications. By analyzing the characteristics of these applications, the algorithm allocates resources to meet latency requirements, reducing delays and improving Quality of Service for critical applications (Tsai *et al*., 2018).

- **Reinforcement Learning for Dynamic Resource Allocation in FlyNets with Mobility Prediction**: Exploring reinforcement learning, the paper of (Cui *et al*., 2023) allows drones to learn optimal strategies for resource allocation based on past experiences and mobility predictions. The algorithm adapts to changing network conditions, with experimental results showing it outperforms traditional methods in dynamic scenarios.
- **Online Machine Learning for Context-Aware Resource Allocation Adaptively to Changes in Network Condition of FlyNets:** This work pursued online machine learning for context-aware resource allocation in real-time changes of network conditions. Since this algorithm learns from the data of real time continually, decisions of allocations become responsive to dynamic changes, hence enhancing resource efficiency and improving performance in networks (Hassan *et al*., 2024).

3.4 Other Relevant Works

- **UAV Trajectory Optimization for Efficient Resource Allocation in FlyNets**: This study proposes an optimization framework for UAV trajectory to balance energy consumption and communication quality. Optimized flight paths ensure that drones maintain optimal positions for resource sharing, leading to improved energy efficiency and communication reliability (Huang *et al*., 2020).
- **Cooperative Task Scheduling for Resource Allocation in FlyNets** Focusing on cooperative task scheduling, drones are enabled to coordinate their tasks, leading to optimized resource usage and minimized conflicts. The system aligns task schedules to reduce delays and enhance network performance, as demonstrated by simulation results.
- **Adaptive Load Balancing for Resource Allocation in Drone Networks**: Presenting an adaptive load balancing algorithm, this work distributes resources evenly across drones, preventing overloads and ensuring efficient utilization. The algorithm adapts to changing conditions, effectively balancing the load and improving network stability (Jiang *et al*., 2020).
- **Blockchain-Based Secure Resource Allocation for FlyNets** (Xu *et al*., 2020): Introducing a blockchain-based framework for secure and transparent resource allocation, this paper ensures trust and integrity in the process. Smart contracts automate allocation, enhancing security and efficiency. The study shows improved trust among drones and prevents malicious activities.
- **Cognitive Radio-Based Resource Allocation in FlyNets**: This research employs cognitive radio technology to enhance resource allocation by allowing drones to dynamically access underutilized spectrum. The algorithm optimizes spectrum usage and reduces interference, adapting to changing conditions and improving communication quality (Ahmad *et al*.,2015).
- **Multi-Objective Optimization for Resource Allocation in FlyNets**: Proposing a multi-objective optimization framework (Midya *et al*., 2018), this paper considers factors like energy consumption, latency, and communication quality in resource allocation. By balancing various performance metrics, the approach meets diverse network requirements, achieving better overall performance.
- **Context-Aware Resource Allocation Using Edge Computing in FlyNets**: Exploring the integration of edge computing with context-aware resource allocation, this work enhances processing capabilities and responsiveness. Edge nodes provide real-time

insights for allocation decisions, reducing latency and improving efficiency in high data processing scenarios (Liao *et al*., 2019).

- **Swarm Intelligence-Based Resource Allocation for FlyNets**: Utilizing swarm intelligence techniques (Udgata *et al*., 2010), this paper leverages the collective behavior of drones for optimized resource distribution. The decentralized approach enables efficient and scalable allocation, improving adaptability and robustness in dynamic environments.
- **Real-Time Resource Allocation in FlyNets Using Fog Computing**: Investigating the use of fog computing for real-time resource allocation, this work provides low-latency and context-aware allocation decisions. By processing data at the network edge, the algorithm reduces latency and enhances resource allocation efficiency in latency-sensitive applications (Subbarai *et al*., 2023).

4. Initial Algorithm for Resource Sharing in FlyNets

The primary objective of resource-sharing algorithms in FlyNets (drone networks) is to allow multiple sites (drones) to share resources without conflicts, while minimizing the number of messages exchanged. In ad hoc mobile networks, the AODV (Ad hoc On-Demand Distance Vector) routing protocol identifies the shortest path between two nodes before establishing communication. We extend this principle to optimize resource allocation in FlyNets.

4.1 Overview and Objectives

In our initial algorithm, we aim to leverage the AODV protocol to minimize message exchanges for each resource request. The algorithm integrates resource availability information into the routing table of each drone, thereby providing a comprehensive view of the network's resource distribution. The network comprises N drones (sites) that share X resources among them, necessitating a system that ensures exclusive access to these resources.

4.2 Token Management and Resource Allocation

To manage resource allocation, we use X tokens, each representing a unique resource. Initially, these tokens are distributed among different drones. When a drone needs to enter the critical section (CS) to access a resource, it sends a request to the holder of the nearest token. This nearest token information is derived from the drone’s routing table, which maintains real-time updates of the network’s topology and resource locations.

Upon receiving the token, the requesting drone gains access to the resource. After utilizing the resource, the drone follows a decision protocol: it may either retain the token for future use or pass it to another requesting drone, depending on the current network conditions and resource demands.

4.3 Handling Network Partitioning

Our algorithm assumes that the routing table of each drone provides a complete and accurate view of the network. However, network partitioning can disrupt this assumption. Partitioning occurs when the network splits into isolated segments, causing some drones to become unreachable by others. This scenario directly affects the routing tables, leading to incomplete information and potentially invalidating the algorithm's effectiveness. Partitioning introduces two major challenges:

1. Routing Table Incompleteness: When drones become unreachable, the routing tables no longer reflect the true network topology, leading to incorrect resource requests and allocations.
2. Token-Resource Disparity: The number of tokens and resources within each partition may differ, causing inconsistencies in resource access and potential conflicts.

4.4 Enhanced Algorithm for Partitioned Networks

To address these challenges, we propose an enhanced version of our initial algorithm that ensures its robust operation even in the presence of network partitioning. This enhanced algorithm comprises the following key components:

- Dynamic Routing Table Updates: Each drone continuously updates its routing table to reflect real-time changes in network topology. This involves periodic broadcasting of network status and resource availability information, ensuring that each drone has the most accurate and current view of the network.
- Token Redistribution Protocol: In the event of network partitioning, a token redistribution protocol is activated. This protocol dynamically reallocates tokens based on the current network topology and the number of drones in each partition. The goal is to maintain a balance between the number of tokens and the number of resources within each partition, ensuring consistent and fair resource access.
- Partition Detection Mechanism: The algorithm incorporates a partition detection mechanism that promptly identifies network partitions. This mechanism relies on monitoring communication patterns and network connectivity. When a partition is detected, the algorithm triggers appropriate responses to re-establish communication paths or adjust token distribution.
- Fallback Communication Channels:To mitigate the impact of partitions, the algorithm includes fallback communication channels. These channels use alternative communication methods, such as satellite links or ground-based relay stations, to maintain connectivity between isolated partitions. This ensures that critical resource allocation messages can still be exchanged, even in severely partitioned networks.
- Adaptive Resource Request Strategy:The resource request strategy is adapted to consider the likelihood of partitions. Drones prioritize requests to nearby tokens and use probabilistic models to predict the availability of resources based on past network behavior and current topology changes.
- Energy-Efficient Communication:The algorithm incorporates energy-efficient communication techniques to minimize the power consumption associated with frequent routing table updates and token exchanges.

The proposed enhancements to our initial algorithm ensure that it can handle the dynamic and often unpredictable nature of FlyNets. By incorporating dynamic routing table updates, a robust token redistribution protocol, partition detection mechanisms, fallback communication channels, adaptive resource request strategies, and energy-efficient communication techniques, the algorithm maintains efficient and consistent resource allocation. These enhancements ensure multiple resources allocation and minimize message exchanges, even in the presence of network partitioning and other challenges inherent to mobile ad hoc networks.

This advanced algorithm paves the way for more reliable and efficient resource sharing in FlyNets, supporting a wide range of applications from surveillance and environmental monitoring to disaster response and beyond.

5. Basic Idea of the New Proposal

FlyNets, or drone networks, present unique challenges in resource allocation due to their dynamic and decentralized nature. Our improved algorithm addresses these challenges by ensuring resources allocation and maintaining consistency between resources and tokens, even during network partitioning. This section details how to apply the improved algorithm in FlyNets, considering the specific characteristics and requirements of such networks.

5.1 Basic Idea of the New Proposal

The enhanced algorithm aims to ensure that the number of resources and tokens in each partition is equal, thus maintaining system consistency and functionality. This involves removing extra tokens or creating new ones as necessary. The required information is inferred from the routing table, which includes new fields added to each node:

Tpres: Indicates the presence of tokens.

Rpres: Indicates the presence of resources.

Sitelead: Indicates whether the node is a group leader.

When a node detects a network partition, it becomes the leader of its partition. The leader informs all nodes in its partition about the partitioning and requests them to update their routing tables. If there is a discrepancy between the number of resources and tokens, the leader sends an update message to align the counts. Nodes then send confirmation messages to the leader, ensuring the number of tokens and resources match within the partition.

5.2 Proposal Details

The system consists of N drones (sites) numbered from 1 to N, and X resources. To ensure multiple resources allocation, X tokens are initially distributed randomly among the sites.

<u>A. Local Variables</u>

Each node maintains the following new local variables:

Leader: A Boolean variable initialized to False, indicating whether the node is a group leader.

Create: A Boolean variable initialized to False, indicating if the node is creating or deleting a token.

<u>B. Messages Used</u>

Two types of messages are used to handle partitioning:

Update_request(): Sent by the leader node to other nodes, indicating the presence of a partition and prompting routing table modifications.

Response(create, i): Sent by nodes holding a token or resource to the leader node to confirm the routing table modification.

<u>C. Proposal Functionalities</u>

The algorithm involves several procedures to manage resource allocation and ensure consistency during network partitioning.

<u>Procedure 1: Collecte()</u>

This procedure iterates through the routing table, incrementing Counter_T for each token and Counter_R for each resource. The totals represent the number of tokens and resources in the partition.

```
Procedure 1: Collecte ()
Begin
        Counter_T :=  0;
        Counter_R :=  0;
    for I := 1 to N do
        if (AODV_[I,Tpres] = 1) then
            Counter_T := Counter_T + 1;
        end if
                if (AODV_[I,Rpres] = 1) then
            Counter_R := Counter_R + 1;
        end if
    end for
End;
```

Procedure 2 Test():

This procedure compares the token and resource counts. If they differ, an Update_request() is sent to all nodes in the partition.

```
Procedure 2: Test ( );
Begin
   if (Counter_T≠ Counter_R) then
          Send Update_request ( ) to all nodes in the
 partition;
    end if
 End;
```

Procedure 3: Receiving Update_Request()

Upon receiving an Update_request(), nodes adjust their Leader and Sitelead statuses. If a node has a resource without a token, it creates a token (Create := true) and sends a confirmation. If a node has a token without a resource, it deletes the token (Create := false) and confirms the deletion.

Procedure 3: Receiving **Update_Request ( );**

```
Begin
    Leader:=  False;
    AODV[I, Sitlead]:=0;
    if (AODV[I, Tpres] = 0 or AODV[I, Rpres]=0) then
        if (AODV[I, Rpres] = 1) then
            (AODV[I, Tpres] := 1;
            Create:= true;
            Send Response(Create, i) to L;
            Else
            if (AODV[I, Tpres] = 1 then
                (AODV[I, Tpres] := 0;
                Create := false;
                Send Response ( Create, i) to the leader;
            end if
        end if
    end if
End;
```

Procedure 4: Receiving Response(Create, i)

This procedure updates the counters based on the Create status received in the response message, ensuring the token and resource counts are balanced.

Procedure 4: Receiving **Response (Create, i);**

```
Begin
    if (Create= true) then
        Counter_T := Counter_T + 1;
        Counter_R := Counter_R + 1;
    end if
End;
```

6. Application in FlyNets and Implementation Steps

1. Integration with AODV: Modify the AODV protocol to include the new fields (Tpres, Rpres, and Sitelead) in the routing table. Ensure that routing table updates propagate these fields across the network.

2. Detecting and Handling Partitions: Implement a mechanism to detect network partitions based on communication failures and topology changes. When a partition is detected, the node automatically assumes the role of the leader for its partition.
3. Token and Resource Management: Ensure each node accurately updates its Tpres and Rpres fields based on its token and resource status. Use the procedures (Collecte, Test, Receiving Update_Request, and Receiving Response) to manage tokens and resources within each partition.
4. Leader Election and Coordination: Implement a robust leader election protocol to handle scenarios where multiple nodes detect partitioning simultaneously. The elected leader coordinates the token and resource updates, ensuring that all nodes in the partition are synchronized.
5. Communication Protocols: Use reliable communication protocols to send Update_request() and Response() messages, ensuring that all nodes receive and acknowledge updates. Implement fallback mechanisms to handle message losses and ensure the consistency of updates.
6. Energy Efficiency and Scalability: Optimize the frequency of routing table updates and message exchanges to conserve energy, crucial for battery-powered drones. Ensure the algorithm scales efficiently with the number of nodes and partitions, minimizing overhead and maintaining performance.

Example

Consider a FlyNet consisting of 50 drones, each capable of carrying out surveillance and data collection tasks. These drones share 10 unique resources (e.g., high-resolution cameras, sensors). Initially, 10 tokens are distributed randomly among the drones.

- **Initial State**: Each drone updates its routing table with Tpres and Rpres fields, indicating the presence of tokens and resources. Drones communicate and exchange tokens as needed to access resources for their tasks.
- **Network Partition**: A sudden storm causes the network to split into two partitions, each with 25 drones. Drones in each partition detect the partitioning through communication failures.
- **Leader Election and Coordination**: In each partition, one drone becomes the leader. The leader in Partition A detects a discrepancy: 7 tokens and 5 resources. The leader in Partition B detects: 3 tokens and 5 resources.
- **Updating Routing Tables**: The leader in Partition A sends Update_request() to all drones in its partition, instructing them to update their routing tables. Drones in Partition A identify the excess tokens and adjust accordingly, either by deleting extra tokens or creating new ones.
- **Ensuring Consistency**: After adjustments, both partitions have matching numbers of tokens and resources. The drones continue their tasks with the updated and consistent resource allocation.

By following these steps, the improved algorithm ensures efficient and consistent resource allocation in FlyNets, even in dynamic and partitioned environments. This approach maintains system stability, supports efficient resource usage, and adapts to the unique challenges of drone networks.

7. Simulation Results

7.1 Simulation Parameters

To conduct our simulation, we defined two categories of parameters: fixed parameters, which remain constant throughout the simulation, and varied parameters, which change in each scenario.

Fixed Parameters:

- Network Area: The simulation was conducted over an area of 960m by 800m.
- Routing Protocol: We used the AODV (Ad hoc On-Demand Distance Vector) Reactive Protocol.
- Propagation Model: The Two-ray ground propagation model was employed, a standard model in mobile network research.
- Mobility Model: The Random Waypoint model was selected. In this model, nodes are distributed uniformly across the simulation area, with their initial positions and subsequent movements being random.

Varied Parameters:

- Communication Range: This parameter was set to either 100 meters or 200 meters.
- Number of Sites in a Partition: The number of sites (drones) within each network partition.
- Number of Tokens in a Partition: The number of tokens available in each partition.
- Number of Resources in a Partition: The number of resources accessible in each partition.

7.2 Simulation Results

To evaluate the performance of the proposed algorithm and identify the parameters influencing its performance, we devised three simulation scenarios. In each scenario, we altered one varied parameter while keeping the others constant.

The proposed algorithm was validated through simulation using the defined scenarios The simulation results provide a comprehensive evaluation of the proposed algorithm's performance under various network conditions.

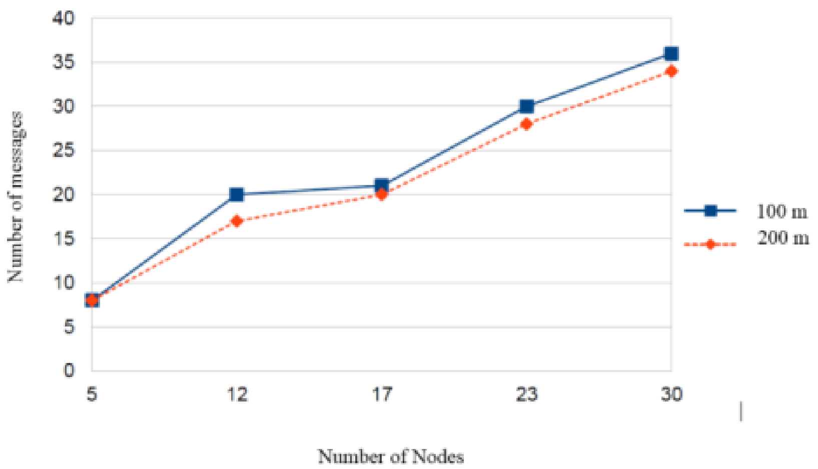

Figure 1-Influence of number of nodes

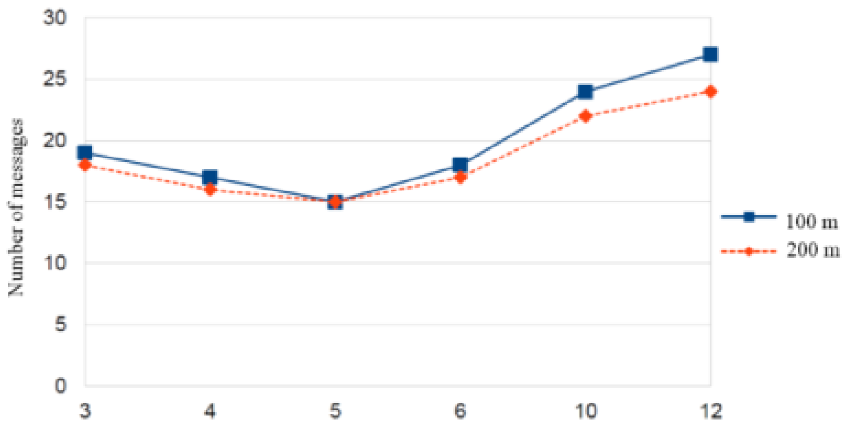

Figure 2 - Influence of number of tokens

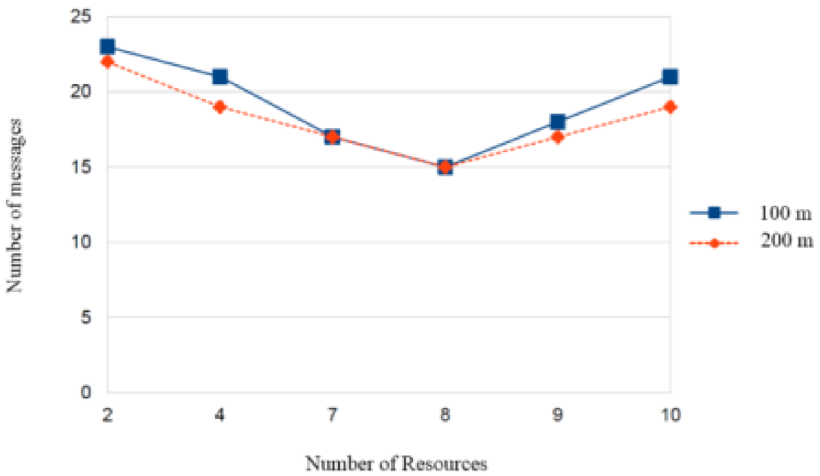

Figure 3 - Influence of number of resources

By varying key parameters such as the number of nodes, tokens, and resources, we were able to observe how these factors influence the algorithm's effectiveness in resource allocation and communication efficiency.

Influence of Number of Nodes: As depicted in Figure 1, there is a noticeable increase in the number of messages exchanged as the number of nodes in the network grows. This trend highlights the algorithm's ability to manage communication in increasingly dense network environments. The rise in message count is attributed to the need for disseminating resource information and maintaining network coordination across all nodes. However, the algorithm efficiently controls this communication overhead, ensuring that the network remains functional without excessive message traffic.

Impact of Communication Range: The simulation reveals an inverse relationship between the communication range and the number of messages. With a larger communication range, the network requires fewer hops to transmit information, thereby reducing the overall message count. This efficiency indicates the algorithm's adaptability to different operational environments, optimizing communication based on the network's spatial configuration.

Influence of Number of Tokens: Figure 2 illustrates the effect of varying the number of tokens on message exchange. Initially, as the number of tokens increases, the message count decreases, reaching a minimal level when the number of tokens aligns with the number of resources. This equilibrium state minimizes message exchanges by ensuring that resources are readily accessible, reducing the need for extensive token redistribution. However, when there is a significant disparity between tokens and resources, the algorithm engages in more exchanges to maintain balance, leading to an increase in the number of messages.

Influence of Number of Resources: Similar to the number of tokens, the variation in the number of resources, as shown in Figure 3, follows a pattern of initial decline in message count, stabilization, and eventual increase. This behavior underscores the algorithm's capability to dynamically adapt to resource availability, ensuring efficient distribution and minimizing communication overhead.

Overall, the simulation results affirm the effectiveness of the proposed fault-tolerant algorithm in maintaining optimal resource allocation in FlyNet's dynamic environment. The algorithm demonstrates robustness in managing communication traffic, even as network density and resource distribution fluctuate. Its adaptability to different communication ranges and resource scenarios further establishes its potential for deployment in various aerial network applications.

8. Conclusion

In this study, we introduced an adaptive fault-tolerant resource allocation protocol for FlyNet, a dynamic aerial network. By addressing the challenges of airspace partitioning and resource management, the proposed algorithm ensures consistent and efficient resource allocation through dynamic adjustments and fault tolerance mechanisms. Simulation results validated the protocol's effectiveness in maintaining network performance, minimizing communication delays, and optimizing resource utilization in the face of mobility and partitioning challenges. Future research will focus on enhancing the algorithm's scalability and security, extending its applicability to a wider range of aerial communication scenarios. The proposed solution lays the groundwork for advancing seamless and reliable connectivity in the rapidly evolving domain of aerial networks.

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