Dynamic Leader Selection in a Master-Slave Architecture-Based Micro UAV Swarm

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***Abstract*—In this paper, we present a method for dynamically selecting leaders in a master-slave communication model in a swarm of micro-Unmanned Aerial Vehicles (UAVs). With the growing size of the UAV swarm in complex missions, it becomes a challenge to control them for efficient execution of missions. In a traditional centralized communication model where all UAVs in the swarm are controlled directly through ground control, channel capacity limits the number of UAVs in the swarm which restricts the scalability. In the context of low-power miniature drones, we limit the communication of the ground Base Station (gBS) with only one UAV (leader) which controls the rest of the UAVs (followers). Towards this, we propose a greedy heuristic method for selecting the UAV leader that requires minimal time to communicate with the gBS in real-time. The proposed master-slave model enhances the scalability of the swarm by improving the utilization of channel resources. Simulation results demonstrate that the proposed dynamic leader selection enhances the lifetime of the entire network with a multifold decrease in energy consumption, compared to the state-of-the-art. Additionally, the lifetime of the network also decreases on operating with a single UAV leader. We also observe reductions in delays by almost 60% and an increase in data rate by 50%.**

***Index Terms*—Unmanned Aerial Vehicles, Internet of Things, Dynamic leader selection, Greedy heuristic solution**

I. Introduction

Micro-Unmanned Aerial Vehicle (UAV) swarms find scope in collaborative missions like delivery of heavy payloads, search and rescue, target tracking, area surveillance, agricultural activities, military operations, and others, which are difficult to accomplish by a single independent UAV. These UAVs need to communicate among one another for maintaining coordination and this interaction may be achieved explicitly through a centralized UAV to the ground Base Station (gBS) using a star topology. The UAV leader needs to receive commands from the gBS and then forward it to the rest of the UAVs (followers). However, a single leader drone does not suffice for the entire duration of the UAV flight due to factors such as depleting energy, communication links, and others in addition to single point of failure. In such scenarios, a dynamic selection of a UAV leader according to changing conditions is necessary for reliable communications.

In this work, we propose a master-slave communication model for relaying the commands from the gBS to the UAVs in the swarm with dynamic declaration of the UAV leader. We consider a gBS which sends commands to the UAV leader,

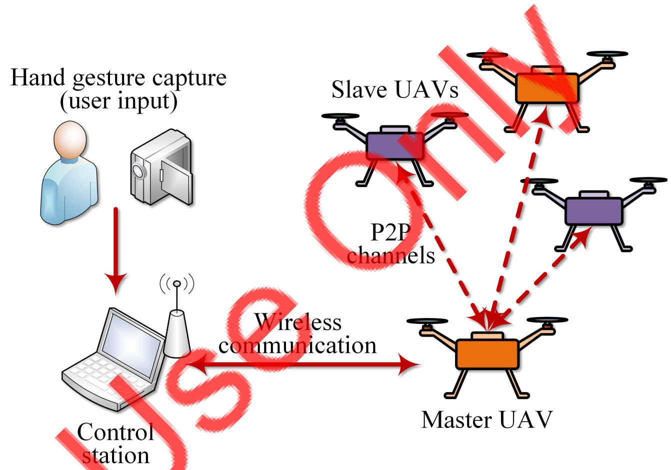


Figure 1: Master-Slave micro UAV swarm communication model for dynamic UAV leader selection.

which relays the same to the follower UAVs to collaboratively complete the designated tasks. As shown in Fig. 1, the followers do not attempt to contact the gBS and vice versa. They interact with the leader using peer-to-peer communications. Such role allocations among the UAVs saves channel bandwidth for communication with gBS as only single UAV (leader) uses the channel directly. However, as the leader may lose contact with the gBS due to reasons like depleting battery, poor connectivity, damage to the UAV, and others, we propose the dynamic selection of a new master UAV. We consider the channel conditions and the delays among eligible UAVs and determine the optimal choice using a heuristic method. While complex optimization techniques such as linear programming may be a viable choice, they add computational overheads in highly dynamic UAV networks. We account for the delays and adopt a greedy heuristic method for making our decision on the UAV leader. The proposed solution has the potential to increase the reliability of the UAV swarm. Additionally, as the UAV leader keeps changing under unfavourable conditions, it increases the lifetime of the swarm.

Example Scenario: As shown in Fig. 1, we consider the setup from our previous work in [1]. The user uses hand gestures to send commands to the UAV leader and assumes the role of a gBS. The leader relays the received commands to the neighboring UAVs. As the conditions change and the leader can no longer take the lead, the proposed solution helps in assigning another UAV as the master, such that the performance of the swarm remains unaffected. The former leader may continue to work as a follower (if possible) or return to its base.

A. Motivation

UAV-swarm operated missions typically depend on ground control for better execution of the task. However, due to constrained channel conditions and device limitations, maintaining coordination in the swarm is challenging. Star topology is a viable solution to overcome such challenges as it reduces the network requirement and avoids the need for multiple points of contact. Solutions depending on multi point contacts need to account for the synchronization necessary for each of the UAV to act on time. However, operating as a leader, especially in a UAV swarm, needs resources, which reduces the lifetime of the entire network. These issues act as motivation for developing the proposed system as a solution for selecting UAV leaders on the fly.

B. Contribution

In this work, we present a systematic communication model to control the UAV-swarm using a master-slave network architecture and select the UAV leader dynamically. The specific contributions in this work are:

- ***Communication Network Architecture:*** We propose a master-slave model for interaction with the swarm to provide better control for large swarms where the delay or weak communication is the major problem using direct centralized control.
- ***Dynamic Leader Selection:*** The proposed master-slave network selects the UAV leader dynamically to ensure reliable and stable communication with the swarm. If the leader or the gBS detects an unstable communication, the proposed model selects a new UAV leader. The selection criteria may differ depending on the task and the environment of the swarm.
- ***Evaluation:*** We evaluate the proposed work and present a comparison with the current state-of-the-art solution and discuss our observations.

It may be noted that there exist multiple optimization techniques for solving the same. However, they incur overheads due to computational complexities. Since we consider low-power miniature drones such as crazyflie, we attempt to avoid such delays by adopting a greedy heuristic method to realize the proposed solution.

II. Related Work

In this section, we present some of the existing work in literature in terms of coordination in the swarm and gesture-based control in UAVs.

A. Swarm Interaction

Multi-UAV swarm interaction and communication is an active area of learning for designing efficient protocols to control the swarm of UAVs. Bogdanowicz [2] proposed a framework for maneovering UAVs in a collisionless and persistent manner without the need for specialized sensors and synchronization. Preiss *et al.* [3] defined a system architecture of a large swarm of mUAVs to fly in a dense formation indoors, they flied 49 mUAVs in a centralised control manner using external motion capture system for object tracking and communication. Punpigul and Thammawichai [4] proposed a swarm flight formation using a centralised control system with radio frequency-based loco-positioning system. A broadcasting approach for communication between master and slave UAVs using the slot-access method is described by Yao *et al.* [5], which they used for completely decentralised swarm of mUAVs. They proposed a collision detection method based on energy detection which is independent of valid information exchange to make it more practical and feasible. The authors in [6] proposed a dynamic routing scheme in a Vehicle to Infrastructure (V2I) environment. Anand *et al.* [7] proposed a master-slave swarm communication model for mobile robots, while forming specific patterns around an object with step-wise linear motion. They also incorporated the dynamic declaration of master bot. Ali *et al.* [8] proposed a UAV control network using 802.11ah to increase the range of the network.

B. Visual Gesture Detection-Based Control

Bolin *et al.* [9] proposed a pre-trained CNN based model to extract human pose as gesture from image captured by on-board camera on UAV. Nagi *et al.* [10] also used on-board cameras for human-swarm interaction through gestures, they used special colored gloves and jacket to detect gestures and body motion. A real-time dynamic hand gesture recognition system based on deep learning models was proposed by Hu and Wang [11]. Their method used a Leap Motion Controller as data input device. They analysed three different deep learning neural networks to control the Drone. An image processing based gesture recognition approach described by Dixit *et al.* [12] used image stream from a camera located on a UAV or at the ground control station to extract and detect hand gestures. Their approach used background reduction and analysis of contours to recognize and localize hand in the captured image. Mukherjee *et al.* [1] used a fog-based gesture detection and control system, and a feedback-based stabilization method for a single mUAV. They proposed an image processing approach for gesture detection. They used a colored glove for better object detection. They also proposed a feedback-based stabilization method in addition to mUAVs on-board stabilization system to enhance flight stability.

C. Synthesis

The existing literature offers multiple solutions towards modeling communications in a swarm for better control over the network. Most of these solutions depend on centralized control and describe direct interaction among the UAVs for performing certain tasks or fly in a certain formation. In this work, we attempt to propose a dynamic UAV leader selection method in such similar architectures by mainly accounting for the necessary communication delays of the UAVs with the gBS.

III. Network Architecture

We consider a set of n UAVs $\mathcal{U} = \{u_1, u_2, \dots, u_n\}$ among which one of the UAVs u_l acts as a leader. The leader interacts with a gBS for receiving commands which it relays to the follower UAVs $\{U_f = U - u_l\}$. While the UAV leader and the gBS use long-range communication technologies, the followers interact with the leader through Peer-to-Peer (P2P) channels, as shown in Fig. 1. We describe the proposed UAV leader selection method in the subsequent sections.

IV. System Model

In this section, we describe the proposed method for dynamically selecting the UAV leader. As we seek optimal communications with the swarm, we model our leader selection based on communication time between the gBS and the UAV. In other words, we select a UAV as the leader which takes a minimum amount of time to interact with gBS. We model this communication time as the complete execution of a single command from sending command by gBS to performing an action by the UAV. Consequently, we consider (i) time taken in the uplink channel ($T_{up}^{u_d}$) to receive message by the UAV u_d, (ii) computation time ($T_{comp}^{u_d}$) for the UAV to process the command, and (iii) propagation delay ($T_{prop}^{u_d}$) of the messages between the UAV and gBS. We calculate the total delay T_{u_d} as:

$$T_{u_d} = T_{up}^{u_d} + T_{comp}^{u_d} + T_{prop}^{u_d} \tag{1}$$

We denote $P = \{p_{u_d} | u_d \in \mathcal{U}\}$ as the set of transmission powers of UAVs, such that p_{u_d} is the transmission power of UAV u_d. Since interference due to other UAVs during computing the communication time with UAV u_d weakens the communication channel and increases the delay in communication, we account for the Signal-to-Interference-plus-Noise Ratio (SINR) from gBS to u_d as

$$\gamma_{u_d} = \frac{P_{gBS}\ h_{u_d}}{\sum_{k=1,k\neq u_d}^{U} p_k h_k + \sigma^2} \tag{2}$$

where P_{gBS} is the transmission power of gBS, the first term in the denominator is the accumulated interference caused by all other UAVs except u_d, σ^2 represents the Additive White Gaussian Noise (AWGN) and h_{u_d} is the channel gain between u_d and gBS. From the work of [13], h_{u_d} depends on antenna gains and path loss factors, which is described by free space path-loss model as $h_{u_d} = \beta\, l_{u_d}^{-2}$, where β is reference channel power at $l_{u_d} = 1$ meter. We consider the free space model as we assume that the UAVs have Line of Sight communications with each other. We will address the effects of environments that do not support free space UAV communications in our extended work.

For leader selection, we send a fixed size message $m = \langle m_b, m_c \rangle$ to compute the communication delay of each UAV separately, where m_b is the size of the message in bits, and m_c is the number of computation cycle required to execute the message action by the UAV. For a computation frequency of f_{u_d} on UAV u_d, we calculate the time required for execution on the received message as:

$$T_{comp}^{u_d} = \frac{m_c}{f_{u_d}} \tag{3}$$

On the other hand, we calculate the transmission and propagation delays as:

$$T_{up}^{u_d} = \frac{m_b}{R_{u_d}} \tag{4}$$

$$T_{prop}^{u_d} = \frac{l_{u_d}}{c} \tag{5}$$

where, R_{u_d} is the data transfer rate (calculated as $R_{u_d} = B\log_2(\ 1\ +\ \gamma_{u_d}))$, l_{u_d} is the distance between UAV u_d and the gBS, and c is the speed of light. Using Equations (3), (4) and (5), the total delay may be expressed as:

$$T_{u_d} = T_{up}^{u_d} + T_{comp}^{u_d} + T_{prop}^{u_d} = \frac{m_{u_d}}{R_{u_d}} + \frac{m_c}{f_{u_d}} + \frac{l_{u_d}}{c} \tag{6}$$

We denote a_{u_d} as the master-slave scheduling variable, where $a_{u_d} = 1$ represents u_d is the UAV leader and $a_{u_x} = 0$ for all other follower UAVs ($x \neq d$). Set $A = \{a_{u_d} | u_d \in \mathcal{U}\}$ denotes the master-slave scheduling vector. Also we maintain that our network has only one UAV leader and represent it as:

$$\sum_{u_d \in \mathcal{U}} a_{u_d} = 1,\ \ a_{u_d} \in \{0,1\} \forall u_d \in \mathcal{U} \tag{7}$$

From Equations (6) and (7), we formulate the utility function for the leader selection model as:

$$\mathbb{U} = \sum_{u_d \in \mathcal{U}} a_{u_d} T_{u_d} = \sum_{u_d \in \mathcal{U}} a_{u_d} \Big(\frac{m_c}{f_{u_d}} + \frac{m_b}{R_{u_d}} + \frac{l_{u_d}}{c} \Big) \tag{8}$$

A. UAV Leader Selection

We describe the leader selection model as a problem to select the UAV which takes the minimum communication time to interact with gBS in Section IV. Considering UAVs that have sufficient power in their batteries to complete their tasks and return to base (E^{thres}), we use the utility function $\mathbb{U}$ in equation 8 to define the leader selection problem as:

$$\mathbb{U}_{min} = \min_{A} \mathbb{U}(A) \tag{9}$$

Due to the constraint in Equation 7, Equation 9 is solvable in linear time using Algorithm 1. Algorithm 1 selects the UAV which takes minimum communication time with the gBS. After the leader selection and assigning the others as followers, the proposed model takes input commands from the user for the UAV swarm to perform certain actions (refer Fig 1). After identifying the user's action-based commands, the gBS checks

Algorithm 1: Master Selection

Input: Initial scheduling vector = A; // UAV 1 as leader
Result: A^*; // Optimal scheduling vector of UAVs
Initialization:
A^* = A
current_uav = 1
while *current_uav* $\leq$ *Number_UAVs* **do**
  if $\mathbb{U}(A^*) > \mathbb{U}(A)$ **then**
    $A^* = A$
  end
end

the connection status with the leader UAV. If the connection is stable, it then forwards the commands to the leader UAV. Otherwise, it again selects the leader UAV from the remaining swarm. When the command is sent successfully, the gBS waits for feedbacks from the UAV leader, which is necessary for ensuring the consistency of the actual state of the swarm with that at the gBS.

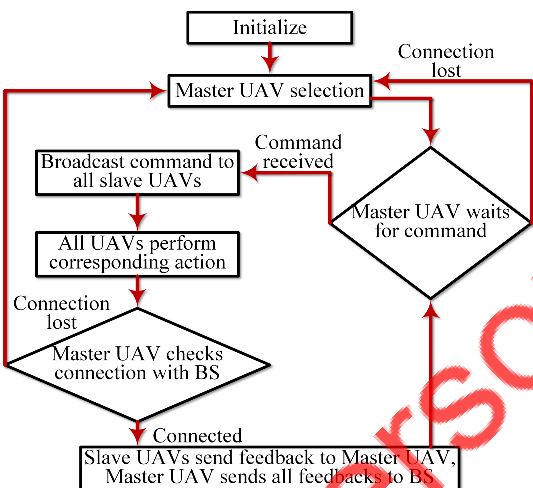


Figure 2: Flow of information in the proposed Master-Slave Swarm network.

Figure 2 illustrates the flow of information among the UAVs in the proposed scheme. After the selection of the UAV leader, the leader waits for commands sent by gBS. If command (message) is received successfully it directly broadcasts it to the other follower UAVs through P2P broadcast channels. The received command is executed by every UAV and a feedback or output message is sent back to the gBS through the leader UAV. Follower UAVs send their feedbacks via the P2P channel to the leader, which then forwards it to the gBS on the leader-gBS radio channel. The network keeps receiving commands from the gBS till the connection between the leader UAV and gBS is stable. If the leader UAV detects an unstable connection to the gBS or if the data transfer rate goes below a certain threshold, then it broadcasts a *connection-lost message* to all other UAVs in the network. Follower UAVs after receiving *connection-lost message* perform leader selection with gBS to declare a new leader UAV and resume their activities accordingly.

V. Results and Discussions

We evaluate the proposed work by simulating it using Python 3.7 on an i5 core processor system. In this section, we study the performance comparison of our model with a centralized control model in a multi-UAV system. We deploy a swam of UAVs in a 100×100 m^2 area and controlled by a single gBS. Both UAVs and gBS have single antennas to communicate. We assume the channel bandwidth of the antenna of both gBS and UAV to be 2.4 GHz (WiFi). We take the reference channel power, β to be -60 dBm, background noise variance σ^2 to be -110 dBm, and c is speed of light equal to 3×10^8 m/s. We consider a uniform transmission power for all UAVs and gBS of 20 dBm. We set the command message size (m_b) to be 64 bytes if not stated otherwise, computation cycles (m_c) to be 8, and CPU frequency of each UAV to be in the range of $50 - 80$ MHz. Fig.3 shows an initial simulation result of

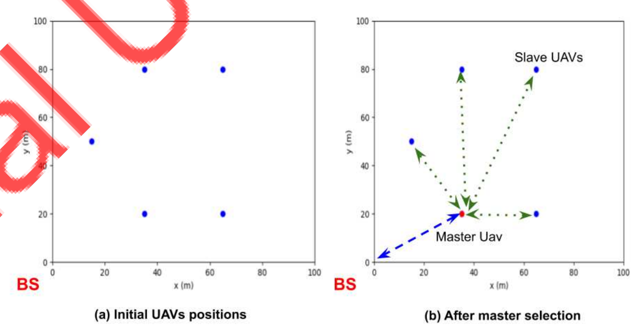
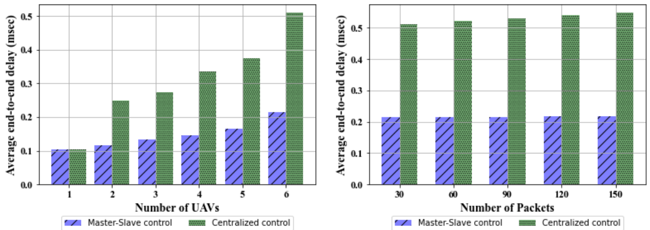


Figure 3: Selection of the UAV leader during simulation.

leader selection process which selects a UAV as leader which has better channel gain and data transfer rate with gBS, and also having minimum communication delay.

A. Benchmark Solution

We compare our proposed system with the work of Punpigul and Thammawichai [4] and refer to it as centralized control. In both models, we consider that the gBS antenna bandwidth is divided equally among UAVs. In other words, each UAV has a bandwidth of B/N units where N is the number of UAVs. Without loss of generality, we follow the same strategy when the UAV leader broadcasts a message to other UAVs. We evaluate (i) the average end-to-end delay, (ii) the average data transfer rate achieved by the BS, and (iii) energy consumption at gBS for transmission of packets while communicating all the command messages with the UAV-swarm.



(a) Varying number of UAVs. (b) Varying number of packets.

Figure 4: Average end-to-end delays.

B. Average End-to-End Delay

We capture the delays by varying both the number of UAVs and packets. Fig. 4a depicts the results of average end-to-end delay with varying number of UAVs. We observe that the end-to-end delay in controlling the UAV swarm is considerably better with master-slave control by almost 57%, compared to the centralized control swarm. We attribute this behavior to the optimal selection of the master UAV. The increase in delay with the increasing number of UAVs is due to a reduction in the bandwidth, leading to low data rates. Figure 4b depicts the result of average end-to-end delay with varying number of packets. Due to the selection of an optimal master UAV, we observe a 60% improvement in the delay. This assures reduced packet drops and collisions. The non-increasing delay suggests the scalability of the proposed work.

C. Average Data Transfer Rate at gBS

The data transfer rate to send data from the gBS depends on the bandwidth of the channel and the interference by other UAVs. We present the average of the achieved data transfer rate by gBS in Fig. 5. We observe a minimum of 50% improvement over the centralized control as the gBS shares its bandwidth among all the UAVs. It may be noted that the data transfer rate decreases with the increase in the number of UAVs because of increased interference and bandwidth sharing. The increase in data transfer rate in the master-slave control model while increasing the number of UAVs from 2 to 3 is due to a change of the master UAV. The newly added UAV in the swarm has a better data rate than the previous UAV leader because of better channel gain, which demonstrates the efficiency of the proposed work. Although small, the newly added UAV also increases the average data rate in the centralized control model.

D. Energy Required at gBS for Transmission

We calculate the required energy for sending packets to the UAVs from the gBS during transmission as:

$$E_{min} = P_{gBS}\ T_{up} \tag{10}$$

where E_{min} is the minimum energy required to send the packet, P_{gBS} is the transmission power of the BS which also varies with channel gain and T_{up} is the time taken to send the

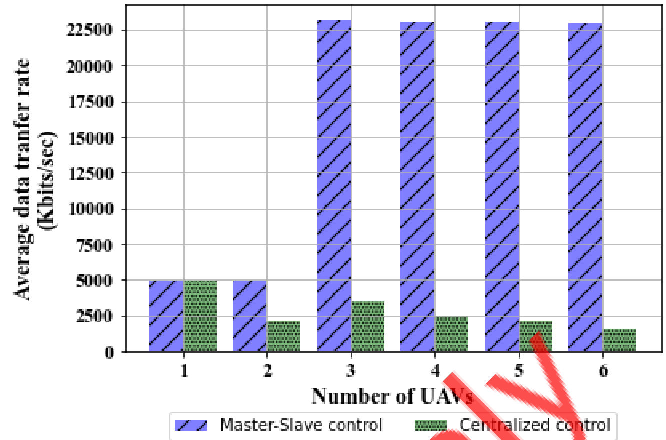


Figure 5: Average data transfer rate achieved by gBS with varying number of UAVs.

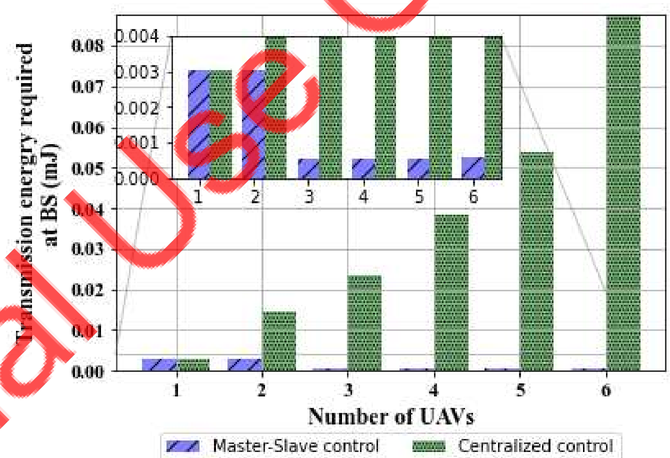


Figure 6: Energy consumption at BS to send packets with varying number of UAVs.

packet. Since gBS sends message to only the UAV leader in master-slave model, we calculate $E_{master-slave}$ as:

$$E_{master-slave} = P_{gBS}\ h_{master}\ T_{up}^{master}$$
$$where,\ T_{up}^{master} = \frac{m_b}{R_{master}} = \frac{m_b}{B\log_2(1+\gamma_{master})} \tag{11}$$

However, in centralized control model, we calculate $E_{centralized}$ as the sum of energies required for all the UAVs

$$E_{centralized} = \sum_{d\in\mathcal{D}} P_{BS}\ h_d\ T_{up}^d$$
$$where,\ T_{up}^d = \frac{m_b}{R_d} = \frac{m_b}{(B/N)\log_2(1+\gamma_d)} \tag{12}$$

where N is the number of UAVs in the swarm. Figure 6 depicts the variation of the energy consumed while sending all the packets to UAVs in a swarm for both models. In the centralized control model, the energy increases with the increasing number of UAVs because of slow transmission caused by increased interference and shared channel bandwidth among them. Sharing of bandwidth accumulates for low data transfer rate, which increases delay and hence requires more energy. In the master-slave model, since bandwidth is not shared with other UAVs apart from the leader, the energy required only varies due to increased interference and change in channel gain. This is the reason why the energy required is almost constant in the case of the master-slave model. The decrease in energy consumption in the master-slave model from 2 to 3 UAVs is because of the change of the UAV leader, which requires less energy due to better channel data transfer rate.

VI. Conclusion

In this work, we proposed a dynamic selection of UAV leaders in a master-slave micro UAV swarm network architecture to enhance reliability and robustness in the communication channel. We make the dynamic selection by considering the quality of the communication channel, its delays, and the transmission power while minimizing the interference in the channel. We evaluated the proposed work on a simulation setup in which all the UAVs in the swarm interact with each other according to the master-slave communication model to perform certain actions based on the commands received from the gBS. We presented a comparison of the proposed model with the existing state-of-the-art solution and highlighted the observed advantages over the latter.

In the future, we plan to extend this work by implementing complex optimization techniques on the same for making better decisions and observe the possible tradeoffs on low-power UAVs. We also plan to address the issue of non-LoS communications among the UAVs

VII. Acknowledgement

The authors gratefully acknowledge the funding received from the INAE Abdul Kalam Technology Innovation National Fellowship, Sanction No. INAE/121/AKF, Dt. 13-02-2019.

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