Research Article

RSSI-Controlled Long-Range Communication in Secured IoT-Enabled Unmanned Aerial Vehicles

Inam Ullah Khan [iD],[1] **Ryan Alturki** [iD],[2] **Hasan J. Alyamani** [iD],[3]
Mohammed Abdulaziz Ikram [iD],[4] **Muhammad Adnan Aziz** [iD],[1] **Vinh Truong Hoang** [iD],[5]
and Tanweer Ahmad Cheema [iD][1]

[1]*Department of Electronic Engineering, School of Engineering and Applied Sciences, Isra University, Islamabad, Pakistan*
[2]*Department of Information Science, College of Computer and Information Systems, Umm Al-Qura University, Makkah, Saudi Arabia*
[3]*Department of Information Systems, Faculty of Computing and Information Technology, King Abdulaziz University, Rabigh, Saudi Arabia*
[4]*Computer Science Department, University College in Al-Jamoum, Umm Al-Qura University, Makkah, Saudi Arabia*
[5]*Faculty of Computer Science, Ho Chi Minh City Open University, Ho Chi Minh city, Vietnam*

Correspondence should be addressed to Vinh Truong Hoang; vinh.th@ou.edu.vn

Unmanned aerial vehicle (UAV) has recently gained significant attention due to their efficient structures, cost-effectiveness, easy availability, and tendency to form an ad hoc wireless mobile network. IoT-enabled UAV is a new research domain that uses location tracking with the advancement of aerial technology. In this context, the importance of 3D aerial networks is attracting a lot of attention recently. It has various applications related to information processing, communication, and location-based services. Location identification of wireless nodes is a challenging job and of extreme importance. In this study, we introduced a novel technique for finding indoor and open-air three-dimensional (3D) areas of nodes by measuring the signal strength. The mathematical formulation is based on a path loss model and decision tree machine learning classifier. We constructed 2D and 3D models to gather more accurate information on the nodes. Simulation findings demonstrate that the proposed machine learning-based model excels in nodes location estimation, the actual and estimated distance of different nodes, and calculation of received signal strength in aerial ad hoc networks. In addition, the decision tree constructs an offline phase control in the flying vehicle's location to enhance the time complexity along with experimental accuracy.

1. Introduction

Due to recent advancements in communication and networking, the flying ad hoc network (FANET) is considered as a more feasible alternative to the wireless sensor network (WSN). To meet growing high-speed networking and communication requirements, unmanned aerial vehicles are the optimal choice for communication. They are used for different cellular network applications such as border surveillance, search operations, crime scene security, home-based security, emergency assistance, and rescue operations. Unmanned aerial vehicles use air-to-air communication (a2a communication) like UAV communicating with other UAVs and air-to-ground communication (a2g communication) like UAV communicating with the ground base station. Air-to-air communication between different UAVs generally requires less energy as compared to air-to-ground communication. UAVs face different challenges such as limited power, short-communication ranges, rapid topological changes, low bandwidth, and handover.

Generally, for radio-range transmission communications, WLAN or WiFi networking is considered, but for long range communication requirements, 802.15.4 is used. WLAN induces heavy overheads due to which it is usually discouraged. Single UAV cannot create FANET; therefore, multiple UAV's are required, and not every UAV needs to be

connected to the base station. UAV does usually have a speed between 30 and 360 km/h due to which communication problems in multiple unmanned aerial vehicles arise. In flying ad hoc networks, there must be a sparse density with a large distance between unmanned aerial vehicles; however, it also depends upon the nature of flying ad hoc networks. The communication between UAV's can be affected due to their high speed, changing topology, changing location, connection failure, and updated processing needed every time. Localization means selecting the location of each UAV even at high speed. There is a need for efficient and accurate localization within short intervals of time according to the high speed.

The weighted centroid algorithm depends upon the beacon frames sent from nodes. These nodes are either expressed in 2D or 3D space. It is measured through the received signal strength identifier (RSSI) for indoor and outdoor environments. This study presents a novel strategy for aerial ad hoc networks using the three-dimensional measurement of received signal strength power which shows optimal outcome in terms of location and the distance of nodes. Calculation of signal strength is performed using a log-normal model. Signal strength plays an important role from aerial vehicles to the land station where cyber-security attacks can be deployed by intruders to overcome and hijack the network which causes disruption. Optimal flying signals transmission mitigates aerial data congestion which reduces many problems in smart cities. Intelligent signaling systems directly mixup in the field of smart cities which improve decision making, the interaction of information, and also smart flying things that increase the behavior of human interaction, energy, and context awareness. The main contributions of this study are as follows.

IoT-based unmanned aerial vehicles are used to improve signal strength in smart cities

Secure communication channels in flying ad hoc networks utilize a two-ray model and centroid algorithm for node localization

Machine learning framework decision tree is applied on the network topology to improve signal strength

Rest of the study is structured with Section 1 which consists of introduction, while Section 2 is composed of brief literature having past data about the problem. Similarly, detailed classification is incorporated in Section 3; also, Section 4 represents the proposed model. Section 5 demonstrates results of the algorithm. The theoretical analysis and future direction is discussed in Section 6, which is explained in conclusion section.

2. Related Survey

In [1], Bilal et al. discussed that the hexahedral method is being replaced by centroid localization algorithms. They compared the performance of the proposed approach with maximum likelihood estimation (MLE); this is further compared with the two-dimensional weighted centroid localization algorithm.

Syed et al. [2] designed a new routing protocol which can select cluster head (CH) for path planning and intelligent routing. The protocol design is based on selecting the group leader in the nodes. The group leader must have some specific attributes or characteristics. The group leader selects nodes and senses the environmental changes; whereas, the OPEN protocol performs better results as compared with the traditional routing techniques which improve energy lifetime.

In [3], Liu et al. compared optimal ant-based distance protocols. The analysis of different protocols is performed by using primary metrics. These routing protocols are evaluated in simulation-based environments, rather than real-time scenario. In this study, almost all of the protocols are based on transition probability, which is pheromone and heuristic-based, and the operation level is energy level control and distance transmission control.

Network topology such as flat and hierarchical describes routing challenges in ant-based protocols. This study also highlights the latest developments in this research field. Pu et al. [4] projected a novel idea in this study. The motivation of the study is a result of rapid development in technology such as sensors and communications in multisized UAVs leading to flying ad hoc networks. Because of the easy deployment of nodes and configurations, FANET is used in many applications such as search operations, rescue operations, and civil family functions. Due to high topological changes in communication links failure, there is an intentional jamming in unmanned aerial vehicles. This work can be further extended by making a connectivity-based mobility model for unmanned aerial vehicles.

Qiang et al. [5] explained the problem of the single connected flying ad hoc network, which can be segmented because of the special attributes of unmanned aerial vehicles. They also described different movements using k hope physical structure; this algorithm is studied in a three-dimensional FANET in numerical computation using a simulation environment. The proposed algorithm is compared with the local and also with the roof of a brief time, offset distance, cascade movement of motes, and also maintaining the original link at the same time.

Guillen-Perez and Cano et al. [6] came up with a new area in the network communication that is flying networks in which we find some different attributes from other areas. This study presents brief literature on mobility models of flying ad hoc networks positioning, propagating proposed for FANETs such as path planning. They used a pure randomized structural approach. In this study, they performed two experiments to advance state of the art by measuring the drones' onboard WiFi radiation patterns. To achieve, this experiment is performed in a controlled environment. Different wireless technologies such as WiFi, LTE, and WiMAX are used. Through these technologies quantifying the influence of radiation pattern onboard communication, the communication is mainly carried out in two-dimensional boundary, but in the future, we can use three-dimensional boundary for this practical experimentation.

Anis and Basit [7] described technical and experimental data on Internet of drones. This technology opens a new

horizon on smart tracking of drones through web and android-based applications using the robot operating system. This study explains object tracking through drones using Internet. Drone tracker uses drone map planner. A cloud-based system manages drones over Internet. Practical experimentation is performed, which shows drone tracking systems with a low speedy destination.

In [8], Zhang et al. [8] presented radio frequency identification for unmanned aerial vehicles that provides 6 degrees of freedom. They attached modern ultrahigh frequency tags that are interrogated. For this purpose, the Bayesian algorithm is used. The proposed experimentation was tested on rich structure for inside environments. SVD-based algorithm and Bayesian filter is used, and this method is efficient for different aerial vehicles. An unscented Kalman filtering mechanism is applied on directional antenna-based aerial networking to estimate the position of unmanned aerial vehicles [9].

According to the past research, we have found that most of the research work was conducted on wireless sensor networks based on the two-dimensional centroid localization algorithm; whereas, we have seen many limitations in the work such as calculating range-based methods; the availability of the data on sensors/hubs is part of range free calculation, and later, the received signal strength power was introduced. Formulation of signal strength on receiving flying nodes makes use of wireless infrastructure which enhances the capabilities of line-of-sight in air-2-ground signals multiplication to maximize the sensor networks. Achieving the optimal signal strength directly increases received signal power; whereby, wireless radio energy of the channel can uphold the power level in flying ad hoc networks. The industrial Internet of things is concerned where communication workstation security and reliable data transmission are the most important factors to safeguard the information centers. Pervasive edge computing is proposed to secure IIoT [10]. However, for lightweight mutual authentication, the client-server model utilizes encryption to secure sessions among the nodes [11, 12]. Threat intelligence can be minimized in dynamic malware analysis using a decision tree to examine behavior and overcome security risks [13]. In the decentralized web of networks, cognitive radio gives optimal results that employ the hidden Markov model to dedicate direct short range communication channels for transmission [14, 15]. Maintain the quality of service in multihop communication to detect Sybil attack; whereas for this purpose, QoS-aware secure communication technique can be easily deployed using Internet of things-based networks, which can be performed on large scale data [16].

3. Detail Classification

3.1. Aerial Networks.
Topology construction plays an important role in aerial networks. In UAV networks, every node is a nonstatic node and moves in three axes. We do a study on how far is the node from the base station and how far is the drone away from the cluster head; for tackling these problems, making topology is important. Kim [17]

discussed that due to rapid fluctuations in topological parameters of futuristic networks, UAV networks are promising technology due to the versatile behavior. This study describes the optimization of topological management to maximize the performance by optimizing the location and movements of unmanned aerial vehicles. It is achieved by adapting the topological changes while carrying out UAV's missions. Therefore, for this purpose, two algorithms were proposed, one for topology construction based on swarm optimization and the second one is adjusting topological changes in flying ad hoc networks, which is based on aerial flying networks. Shi et al. [18] introduced a new area that is a drone-assisted vehicular network (DAVN), which provides connectivity between vehicles and futuristic networks of unmanned aerial vehicles. In [18], they further discussed a brief architecture of software define the drone-assisted vehicular network (DAVN) by cooperating with vehicle infrastructure that can improve connectivity between drones and vehicles. The architecture is constructed on a mobile ad hoc network that includes static nodes and a remote server/node for communication; then, this process was updated into flying ad hoc networks that comprise a base station and drones. A pictorial representation of DAVN is presented in Figure 1.

3.2. Localization.
Localization means to measure the distance between the nodes; there are two types of localization: one is indoor localization and the second one is open-air/outdoor localization. Yves and Peng [19] in their study described that low cost received signal strength can be found by simple experimentation of two devices that will be connected to a database to store the data. The algorithm works on the location of an unknown mote by using the received signal strength indicator (RSSI) with angle-based localization estimation (RALE). RSSI value gets increased when it comes near to hidden workstations which keep away from angle unreliable RSSI. The results obtained after the practical experiment show that RALE only requires RSSI and the angles. It does not require a complex computationally expensive algorithm. Furthermore, they suggested that this research can be tested on the position and height of the node. Wireless sensor networks mostly work in the bounded area of communication that forms clusters; the tracking of a static node or cluster is very easy, and these issues can be tackled by dynamic programming. As communication advances in many areas, hybridization of many heterogeneous sensor networks offers low power in high communication networks. Akter et al. [20] described the tracking and localization algorithm in wireless sensor networks. Due to the drawbacks in the static clustered routing, this research incrementally updates, creates maintenance through online learning, and shows us energy-efficient tracking and localization in wireless sensor networks. Some nodes decrease computational complexity calculation and give us proper information of the coordinate systems. Our research study will make use of signal strength power that shows how much is received which will be opposite to the distance between unmanned aerial vehicles.
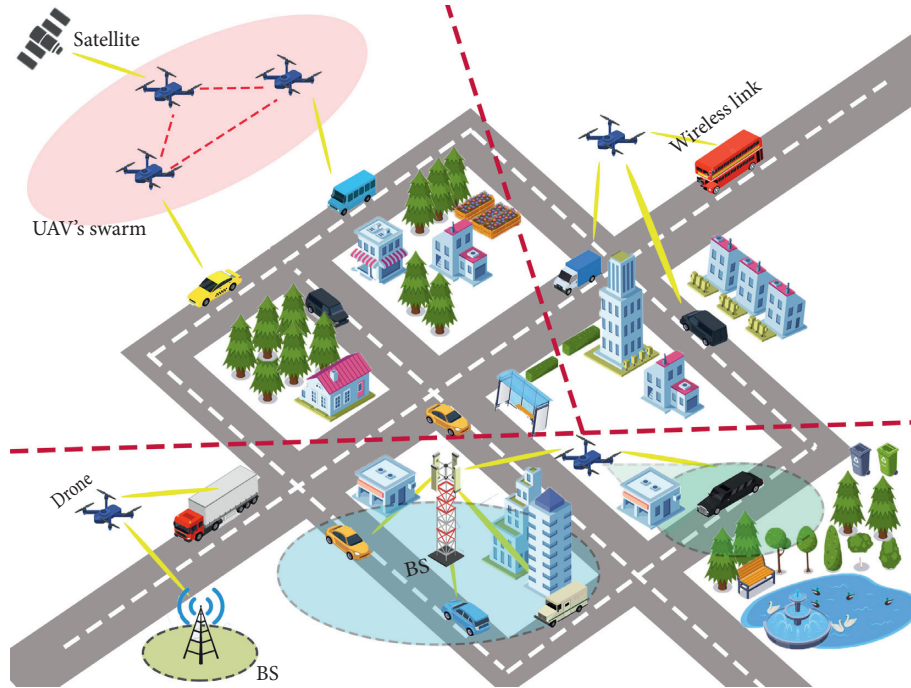
Figure 1: Drone-assisted vehicular networks.

3.3. Localization Strategies and Algorithm.

As discussed in Section 3.2, localization is the estimation of the distance from one node to another node, such as environmental monitoring checking animals' habitat, fire surveillance, water quality checking from where the water is coming, search operations, and intrusion detection systems. Wireless sensor localization is the process to estimate the location of the sensors having unknown locations, time, distance, angle of arrival, and how the motes are connected. As far as the global positioning system (GPS) is a concern, this is very expensive to implement in every mote; so that is why we go for the technique of localization. Sensor with a known location of position information is called anchors. Range free localization includes pattern matching and hop-count-based localization. There is another branch called target/source localization, which includes single and multiple target localizations.

Yu et al. [21] in their study introduced two algorithms that give us better results to localize a node. First, error terms of the estimated distance between anchor motes. Second, the QDV-Hop algorithm minimizes error to obtain optimal localization. Almost both proposed algorithms achieve similar accuracy by solving unconstrained optimization issues. Later, localization can be improved by reducing computational complexity while improving accuracy.

The range free estimation can be expressed using centroid algorithms, DV-Hop, and APTI algorithms. In Figure 2, we briefly presented localization taxonomy that comprises of (i) target/source localization, (ii) distribution, (iii) mobility, (iv) ranging, (v) coordinates, and (vi) location. Figure 3 elaborates the classification of node localization strategies for wireless technology like 802.1, which mainly covers centralized and distributed localization. Distribution

localization techniques further extend to six modules such as bacon based, relaxation based, coordinate system, hybrid, error propagation, and interferometer ranging. Bacon-based techniques have three more modes, which are diffusion, gradient, and bounding box. The 2D view of sensor workstations in flying vehicles gives the flat view where the three-dimensional implication displays a real-time field of vision in the network topology. Deep insight idea of the 3D location where flying nodes is having practical applications is utilizing sensor nodes. Besides, working on 3D-based environments on Internet of drones to improve node localization is a difficult task. Our simulation environment is based on a 3D centroid algorithm which will estimate not only node distance computation but also signal power between two unmanned aerial vehicles to measure the distance between aerial vehicles. Figure 2 represents the taxonomy ladder of localization, where Figure 3 shows wireless sensor communication networks' distribution in terms of centralized or either distributed localization.

3.4. Proposed Model.

Signal strength power measurement commonly known as the received signal strength identifier (RSSI) is a technique for calculating the distance between two UAVs or wireless nodes. Signal strength varies as the distance between nodes changes. However, if you compare it to the real environment, the received signal strength indicator is highly influenced by environmental noise. Gao et al. [22] used a two-ray model for their proposed scheme for node localization. They tested the proposed technique in the rice field. With advancements in wireless communication technologies, there must be some efficient mathematical models that can be used to improve the accuracy in motes
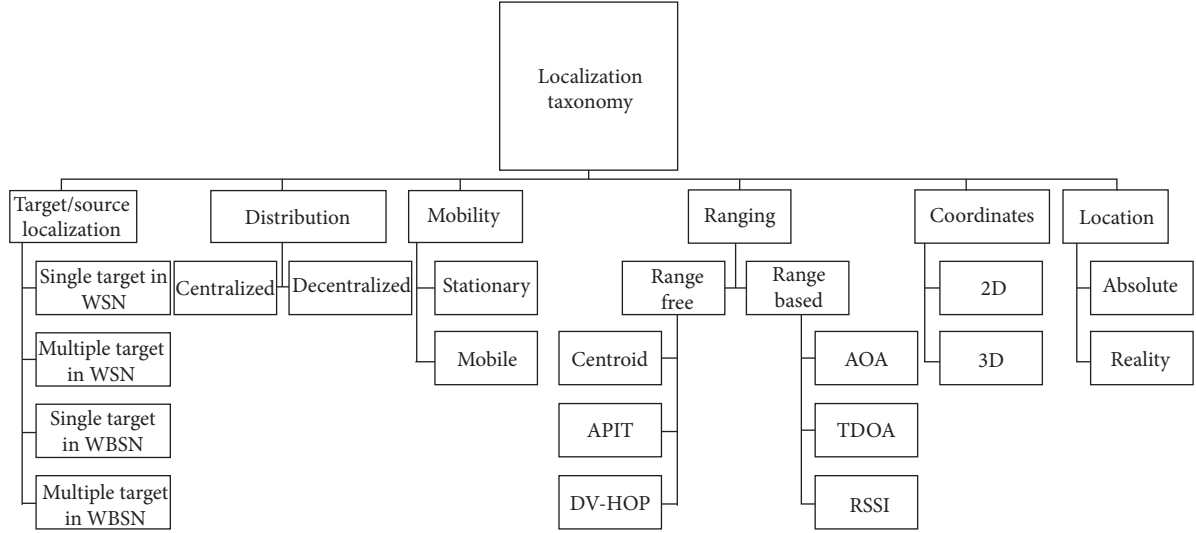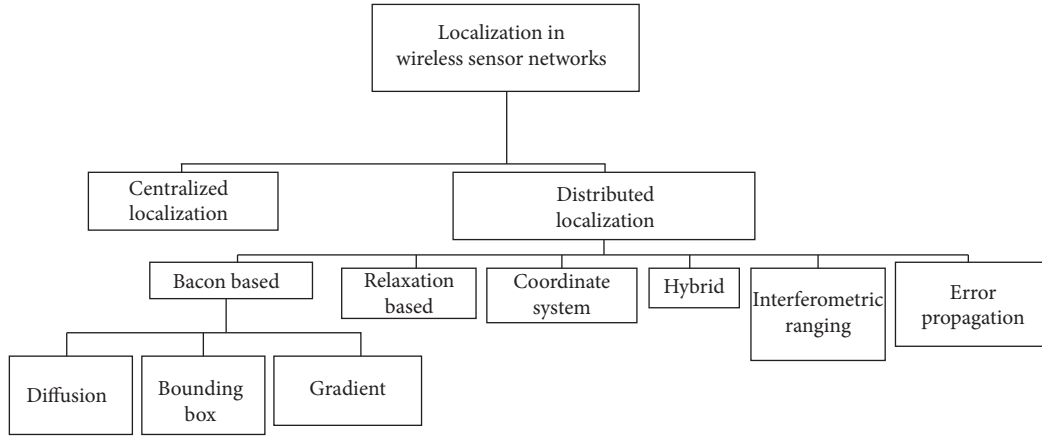
FIGURE 2: Localization taxonomy.

FIGURE 3: Classification of localization in wireless sensor networks.

localization algorithms. Received signal strength measurement is based on distance; we applied this technique in the centroid algorithm for node localization in aerial technology. Figure 4 elaborates the ideal relationship of received signal strength and distance between nodes.

$$\text{RSSI} = -k \log d + a,$$
$$d = 10 \left[\frac{(a - \text{rssi})}{k} \right]. \tag{1}$$

Syed et al. [1] discussed that remote signal plays a vital role in wireless communication; so remote received signals and motes relationship is given in the following equation:

$$P_r = P_t \left(\frac{1}{d} \right). \tag{2}$$

We must take ten times logarithm on both sides and convert it into dBm, as given in the following equation.

$$P_R (\text{dBm}) = A - 10n \log d. \tag{3}$$

Syed et al. [1] further discussed that the above equations are for urban environments, and the equation for received signal strength on the receiver side is given by the following equation.

$$P_r (\text{dB}) P_t G_t G_r * \left(\frac{h_t^{\,2} h_r^{\,2}}{d^4} \right). \tag{4}$$

The shadowing model using signal strength power can be briefly explained using the following equation.

$$P(d) = P(d_0) - 10\eta \log 10 \left(\frac{d}{d_0} \right) + X\sigma. \tag{5}$$

η is the signal attenuation used for some specific environments even when some obstacles come on the path of signal. $X \sigma$ is the Gaussian random variable, for smaller values and larger distances calculation of error for small values of measured signal strength.
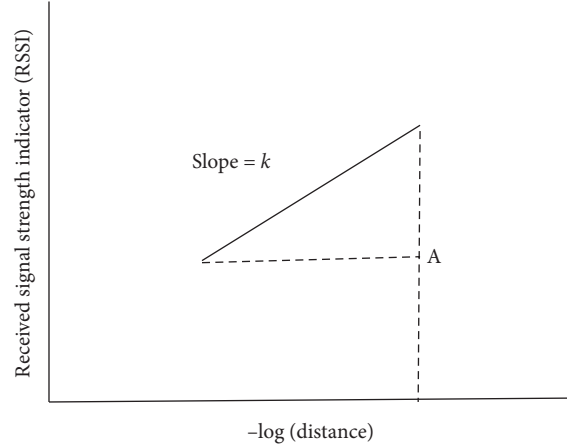
Figure 4: Relationship between RSSI and distance.

$$d = 10 - \frac{(P(d) - P(d_0) - X_\sigma)}{10\eta},$$

$$d = 10 - \frac{(P(d) - P(d_0) + X\sigma 1)}{10} \quad \text{if } P(d) \geq P1, \quad (6)$$

$$d = 10 - \frac{(P(d) - P(d_0) + X\sigma 2)}{10\eta 2} \quad \text{if } P(d) < P1.$$

In wireless communication using static access points, indoor localization is having importance, through which accuracy can be improved. Wang et al. [23] proposed that access point for indoor localization in 2D space is divided by special access points. They suggested that regions are divided by different locations, and the distance of the rank is provided to each region on access point. Location sequenced is obtained by using channel status information (CSI) between the access points. This algorithm is compared with the traditional method, i.e., received signal strength indicator (RSSI), and the simulations results show us accuracy of about 24.31%.

3.5. Wireless Technology. Short range communication is mostly used in aerial technology by using ZigBee. ZigBee is a low cost, easy to configure IEEE 802.15.4-based specification, which is generally used to create personal wireless area networks. It is used in different applications such as agriculture, smart homes, and military. Yu et al. described 3D localization in [24]. It uses a well-known loop invariant technique for division, with reference to point anchor bounded in an outer side using parameter points known as parametric loop division (PLD), for the measurement of noise. In Figure 5, we presented a novel technique called the three-dimensional centroid algorithm and RSSI framework in FANETs.

$$P_L(\text{dB}) = 10 \log Q,$$

$$P_L(\text{dB}) = -10 \log \left\{ \frac{R}{S} \right\}. \quad (7)$$

Let G_t and G_r unite. L does not affect

$$X^2 + Y^2 = M_i^2, \quad i = 1, 2, 3, \ldots,$$

$$X^2 + Y^2 - M_i^2 = 0, \quad \text{If} \neq 0, \text{then} = ei,$$

$$X_i^2 + X^2 - 2X_i X_0 + Y_i^2 + Y^2 - 2Y_i Y_0 - M_i^2 = 0, \quad (8)$$

$$M_i^2 - X_i^2 - Y_i^2 = (X^2 + Y^2) - 2X_i X_0 - 2Y_i Y_0.$$

Using the prior n-1 formulas minus n-1$^{\text{th}}$ formula,

$$X_i^2 + Y_i^2 - X^2 - Y^2 - M_i^2 + M^2 = 2X_0(X_i - X_n) + 2Y_0(Y_i - Y_0),$$

$$AX = B. \quad (9)$$

Basically, A is a tall matrix, whose inverse does not exist; so, premultiply with A^T:
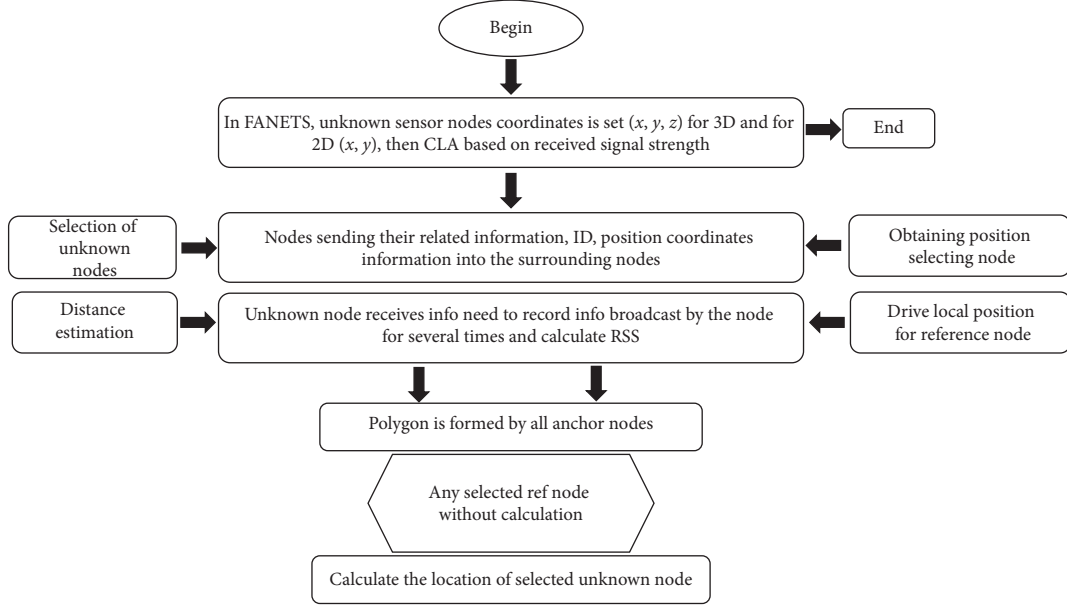
$$A^T A X = A^T B. \quad (10)$$

$A^T A$ = square matrix.

FIGURE 5: Three-dimensional centroid algorithm and RSSI framework in FANETS.

$$X = \left(A^T A\right)^{-1} A^T B. \tag{11}$$

4. Mathematical Formulation for Three-Dimensional (3D) Calculation

$$X_i^2 + X_0^2 - 2X_i X_0 + Y_i^2 + Y_0^2 - 2Y_i Y_0 + Z_i^2 + Z_0^2 - 2Z_i Z_0 = M_i^2,$$
$$\left(X_0^2 + Y_0^2 + Z_0^2\right) - 2X_i X_0 - 2Y_i Y_0 - 2Z_i Z_0 = M_i^2 - X_i^2 - Y_i^2 - Z_i^2. \tag{12}$$

Using the prior $(n\text{-}1)$ formula minus the nth formula,

$$\left(X_0^2 + Y_0^2 + Z_0^2\right) - 2X_0\left(X_i - X_n\right) - 2Y_0\left(Y_i - Y_n\right) - 2Z_0\left(Z_i - Z_n\right),$$
$$X_i^2 + Y_i^2 + Z_i^2 - X_n^2 - Y_n^2 - Z_n^2 - M_i^2 - M_n^2,$$
$$A^T A X = A^T B,$$
$$X = \left(A^T A\right)^{-1} A^T B. \tag{13}$$

5. Simulation Results

We used Matlab for the simulation of the proposed model. We deployed 9 nodes randomly in the topology. All the nodes used in the topology are mobile and move in all three access at the same time. We constructed two scenarios one for 2D space and another for 3D. Pictorial representation of 2D and 3D topologies are presented in Figures 6 and 7, respectively. Few important simulation parameters are presented as follows.

(1) Number of nodes: 9.

(2) Calculation method for RSSI: log-normal method.
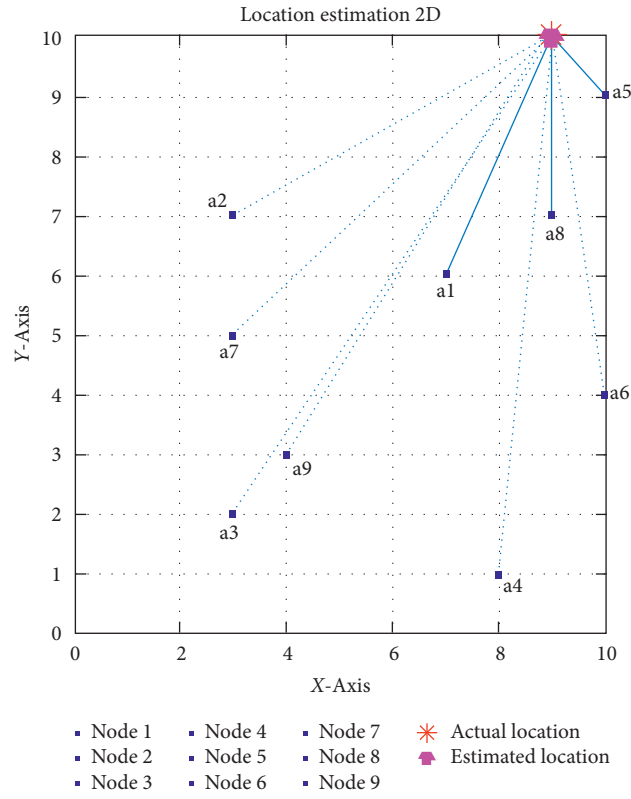
(3) Path loss for reference distance: 55 db.

Location estimation 2D

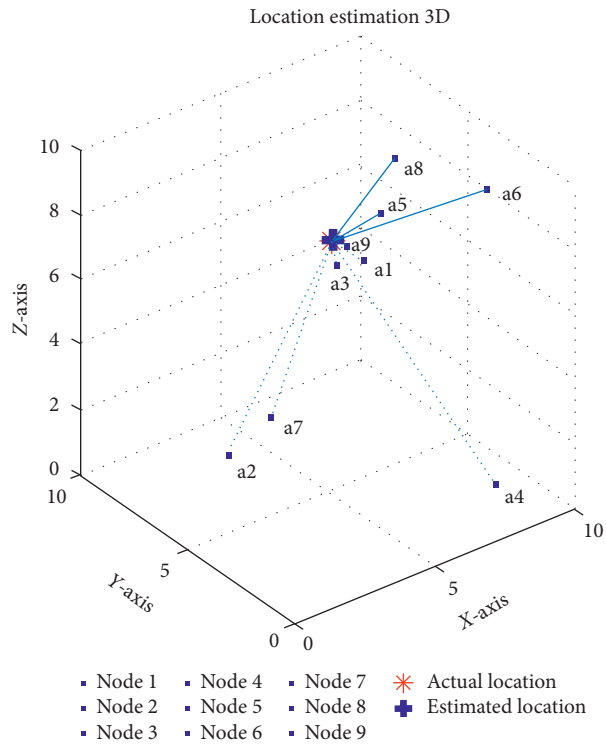Figure 6: 9 UAVs deployed randomly in 2D.

Location estimation 3D

Figure 7: UAVs deployed randomly in 3D.

Estimation of 3D location with the decision tree algorithm for flying Ad hoc networks
Number of nodes: 9
Actual distance from node 1: 2.828427e + 00
Actual distance from node 2: 7.280110e + 00
Actual distance from node 3: 2.236068e + 00
Actual distance from node 4: 7.071068e + 00
Actual distance from node 5: 7.071068e + 00
Actual distance from node 6: 4.690416e + 00
Actual distance from node 7: 5.099020e + 00
Actual distance from node 8: 8.774964e + 00
Actual distance from node 9: 6.557439e + 00
Calculation of received signal strength by the log-normal model
Path loss for reference distance: 55 dB
Path loss exponent: 1
Reference distance: 1 m
Noise variance: 7
Received signal strength from node 1: 5.748455e + 01
Received signal strength from node 2: 5.337862e + 01
Received signal strength from node 3: 5.850515e + 01
Received signal strength from node 4: 5.350515e + 01
Received signal strength from node 5: 5.350515e + 01
Received signal strength from node 6: 5.528789e + 01
Received signal strength from node 7: 5.492513e + 01
Received signal strength from node 8: 5.256755e + 01
Received signal strength from node 9: 5.383266e + 01
Estimated distance from node 1: 5.643454e − 01
Estimated distance from node 2: 1.452573e + 00
Estimated distance from node 3: 4.461542e − 01
Estimated distance from node 4: 1.410864e + 00
Estimated distance from node 5: 1.410864e + 00
Estimated distance from node 6: 9.358610e − 01
Estimated distance from node 7: 1.017388e + 00
Estimated distance from node 8: 1.750836e + 00
Estimated distance from node 9: 1.308381e + 00
Node with good signal strength: node 3
Node with good signal strength: node 1
Node with good signal strength: node 6
Node with good signal strength: node 7
Actual location: (5, 3, 1)
Estimated location with the decision tree algorithm: (5.009588e + 00, 3.019663e + 00, 1.041434e + 00)

FIGURE 8: Decision tree for FANETS (3D).

(4) Path loss exponent: 1.

(5) Reference distance: 1 m.

(6) Noise variance: 7.

(7) Machine learning classifier: decision tree.

(8) Cost function: mean square error.

Figures 8 and 9 are MATLAB generated results which show some parameters such as estimated distance, nodes with signal strength, and actual distance among the aerial vehicles. Figure 8 is utilized for 2D and Figure 9 for 3D using Internet of flying vehicles.

Table 1 shows the comparison between the proposed solution and wireless sensor node localization which represents optimal results by using a decision tree to improve receive signal strength in the dynamic network. Therefore, signal power is improved more while utilizing machine learning technique as compared with the static node localization.

Estimation of 2D location with the decision tree algorithm
Number of nodes: 9
Actual distance from node 1: 2
Actual distance from node 2: 4.123106e + 00
Actual distance from node 3: 2.236068e + 00
Actual distance from node 4: 5
Actual distance from node 5: 5.830952e + 00
Actual distance from node 6: 4.242641e + 00
Actual distance from node 7: 5.099020e + 00
Actual distance from node 8: 7.211103e + 00
Actual distance from node 9: 4.242641e + 00
Calculation of received signal strength by the log-normal model
Path loss for reference distance: 55 dB
Path loss exponent: 1
Reference distance: 1 m
Noise variance: 7
Received signal strength from node 1: 5.898970e + 01
Received signal strength from node 2: 5.584776e + 01
Received signal strength from node 3: 5.850515e + 01
Received signal strength from node 4: 5.501030e + 01
Received signal strength from node 5: 5.434261e + 01
Received signal strength from node 6: 5.572364e + 01
Received signal strength from node 7: 5.492513e + 01
Received signal strength from node 8: 5.341998e + 01
Received signal strength from node 9: 5.572364e + 01
Estimated distance from node 1: 3.990525e − 01
Estimated distance from node 2: 8.226677e − 01
Estimated distance from node 3: 4.461542e − 01
Estimated distance from node 4: 9.976312e − 01
Estimated distance from node 5: 1.163428e + 00
Estimated distance from node 6: 8.465181e − 01
Estimated distance from node 7: 1.017388e + 00
Estimated distance from node 8: 1.438804e + 00
Estimated distance from node 9: 8.465181e − 01
Node with good signal strength: node 1
Node with good signal strength: node 3
Node with good signal strength: node 2
Actual location: (5, 3)
Estimated location with the decision tree algorithm: (5.005643e + 00, 2.995822e + 00)

Mean square error for 3D position: 7.317732e − 04 m
Mean square error for 2D position: 1.643185e − 05 m

Figure 9: Decision tree for FANETS (2D).

Table 1: Comparison of the proposed work with WSN-based node localization.

Ref/Proposed work	Number of nodes	WSN-based node localization	Flying things node localization	Node with good RSS using decision tree and dynamic mobility	Node with good RSS using WSN nodes	2D or 3D
[1]	9	YES	NO	NO	5.704609	Both
Proposed work	9	NO	YES	5.850515	NO	Both

6. Conclusions

Aerial networks refer to flying ad hoc networks or unmanned aerial vehicles. The rapidly changing dynamic structure of drones using different mobility models and topologies makes a challenge in implementing an algorithm that can measure signal strength power accurately. This study implementation presented a theoretical analysis and provided a brief discussion on using the three-dimensional centroid localization technique, step by step sequences using only 9 UAV's which have improved received signals on some UAVs. In the future, we can make use of different locations

on using distinct topological arrangements in aerial vehicles. Simulation results show that our decision tree-based model has shown good potential to address this problem.

Data Availability

This research is based on simulations, which are performed in a simulator. Therefore, there is no dataset used in this research.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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