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Original Article

Coverage Area Maximization for Multiple UAVs Using Co-Operative Game Theory

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Abstract *- Unmanned Aerial Vehicles (UAVs) have been gaining popularity with their distinctive features. A multi-UAV network has an advantage over a single UAV, and they can co-operatively accomplish a complex task.* Ensuring full coverage of the communication area with the least possible UAV deployment is still underexplored. *Non-game theoretic approaches focus on centralized solutions and require constant communication, which is difficult in high mobile UAV communication. Deployment of UAVs in a particular area leads to an increase in interference and therefore reduces network performance. Therefore, in this paper, with the objective of coverage area maximization, a co-operative game theory has been proposed for a multi-UAV scenario in communication with Ground Users (GU). A radio frequency propagation model has been adopted for coverage probability calculation. A Spatial Adaptive Play (SAP) driven algorithm has been formulated for the convergence of the potential game approach to select the game action for the next state. Interference has been mitigated by using the relative distance criterion among UAVs. Nash equilibrium has been proved, and it has been shown that convergence has been reached. Each UAV, according to the co-operative game scenario, tries to maximize utility/payoff.* Simulation results demonstrate that the proposed game theory approach is both reliable and effective.

Keywords *- Co-operative Game Theory, Coverage Maximization, Nash Equilibrium, Potential Games, Unmanned Aerial Vehicle.*

1. Introduction

Unmanned Aerial Vehicles (UAVs), popularly known as drones, have seen rapid adoption for the incoming future technologies. With the special features of UAVs as high mobility, availability, small size, accessibility, robustness, flexibility, and low cost, they are used for different applications, e.g., agriculture, surveillance, monitoring, search and rescue, security, disaster management, delivery of goods and services, visual inspection, emergency medical supply, etc. [1, 3]. UAVs are used basically as air vehicles that fly like normal airplanes but without an onboard pilot. Traditional aircraft are operated by a pilot; this is what makes a UAV different from them. When a UAV is in aerospace, it is called “Platform”. When some external hardware is implemented in it, it will be termed “Payload”. Adding payload to the platform will result in a "Drone" that could be used for various applications, and it will increase its efficiency as well as accuracy.

While UAVs have a lot of interesting features, they also have some challenges of their own, like resource management, deployment in 3D space, path planning, energy-efficient coverage, security, etc. [2, 4]. A single UAV cannot handle complex tasks; therefore, multiple UAVs are needed to form a cooperative team to perform large-scale tasks.

In wireless sensor networks, coverage of every single node is of utmost importance. There could be a possibility that UAVs leave some nodes uncovered, or some nodes could not access the UAV radio range [5]. Therefore, there is a need to co-operatively explore the coverage area.

In a coverage scenario, the deployment issue of UAVs affects the energy, which leads to interference among other neighbouring UAVs. To solve such deployment issues, a suitable approach must be taken into account. In this regard, co-operative game theory plays a very important role in maximizing coverage area under minimum power constraints. In comparison with optimization techniques that require many constraints, game theory is easy to understand, use, and analyze.

In a multiple UAV scenario, interference among mobile nodes as well as among multiple UAVs is an important parameter to consider while working with coverage area problems [6, 7]. Some work has been done on coverage area maximization that has used area partitioning before searching [8], which is a time-consuming and complex task. There is a limited survey on game theory in UAV communication; conventional methods lack the benefits of using game theory as described in [9]. To overcome these research gaps, we have addressed these points in our proposed work.

The major contribution of this research can be outlined as:

- A UAV-to-GU network deployment model has been developed to describe the relationship between UAV-GU, considering the radio pathloss scenario.
- A novel algorithm employing Spatial Adaptive Play (SAP) has been formulated with a relative distance parameter to reduce interference among UAVs.
- Based on the potential game approach, a co-operative game among a multi-UAV scenario has been proposed for maximum coverage with a minimum number of UAVs. Nash equilibrium has been proved, and convergence has been reached.

The article is presented in the following order: Section 2 discusses related work covering coverage and game theory. Section 3 discusses a network deployment model for UAV-GU that has been proposed with a radio frequency propagation model. Section 4 describes the co-operative coverage area maximization game model based on the potential game approach. The proposed study's results are discussed in Section 5, with the concluding remarks presented in Section 6.

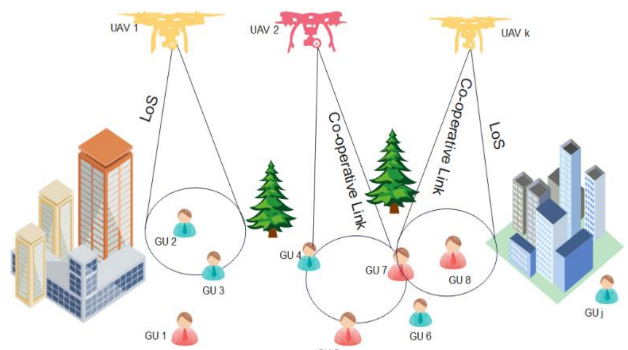

Fig. 1 Schematic diagram for UAV-ground communication

2. State of the Art

2.1. Coverage Problem in UAV-Aided Networks

In wireless sensor networks, one of the known classical problems is the coverage problem of an area. A number of approaches have been investigated to address this issue. UAVs can carry wireless sensors along with them for their mission accomplishment tasks; therefore, the solution to the area coverage problem lies in the UAV networks as well. UAVs have a lot of unique features that add up to new solution ideas. While considering UAVs for area coverage problems, various factors must also be considered, i.e., mobility, battery life, limited communication, obstacles in the mission area, robustness, and delay of coverage algorithms, as illustrated in Figure 1.

A lot of research work has been done in the past addressing the coverage problem in UAV-aided networks. The author in [10] proposed a mathematical model for coverage maximization by optimizing the altitude of UAVs. It was determined that the line of sight between the UAV and the ground node can be presented by an equation considering the projection angle and urban characteristics. The author in [11] derived an optimal placement algorithm aimed at maximizing user coverage while minimizing transmit power. To simplify the placement problem, it was divided into horizontal and vertical dimensions by preserving the optimality scenario.

In the horizontal dimension, deployment was modelled as a circle placement problem and a smallest enclosing circle problem. The results showed that increasing the count of heterogeneous UAVs leads to an increased count of covered users. To enhance UAV user coverage, the connection issue of aerial users served by an aerial base station was investigated [12]. A 3D placement scheme was introduced to enhance the coverage of aerial users while operating under spectrum sharing, taking into account two approaches: orthogonal and non-orthogonal sharing.

For each explored altitude, the horizontal 2D location of the aerial base station and the altitude showing the best coverage are selected. Under orthogonal policy, low altitude and large antenna beamwidth were observed, whereas in non-orthogonal policy, the lowest authorized altitude and narrow antenna beamwidth were observed. There is an improvement in performance if more aerial users form a cluster together [12].

The author has studied a tradeoff between UAV connectivity and area coverage maximization in [13]. Circle packing theory has been used along with the efficient deployment of UAVs to maximize the total coverage area. Coverage maximization was achieved with the least number of UAVs and by adjusting the factors such as the location of UAVs and antenna gain. The aim of UAVs is to achieve the highest network coverage by maintaining the service quality. Considering this, an optimization algorithm for a UAV base station deployment method based on relative distance by maintaining QoS has been proposed [14]. They calculated three types of relative distances based on sensing the coverage boundary, uncovered ground area, and neighbouring UAVs. It is proven that this approach covered 22.4% more coverage than the random deployment of UAVs. Namwar et al. in [15] developed an optimal 3D placement and effective resource allocation method for heterogeneous UAVs under test conditions. Initially, an optimal flight altitude of UAVs considering transmit power and environmental parameters was developed, and after that, they deployed an algorithm to maximize the coverage that also optimizes resource allocation along with the location of UAVs. Namwar et al. in [15] also proposed an optimization algorithm that is composed of two parts: i) an MDP algorithm and ii) an evolutionary algorithm. MDP finds the feasible solution set for optimization, and the evolutionary algorithm searches the obtained feasible set to find the best arrangement of coverage maximization for UAVs.

Previous work on coverage lacks large distributed networks that change dynamically with time, requiring a large number of ground users' coverage. This leads us to explore new network designs for UAVs with much advanced and robust technology.

2.2. Game Theory in UAV-Aided Networks

A single UAV could not meet the requirements of a large, distributed, and dynamically changing network. Therefore, a number of UAVs are required to accomplish complex network demands. Along with the complex and large number of UAVs that arise, there must be co-operation between them so that, with minimum resources, improved efficiency could be obtained. From this perspective, Game Theory in the context of co-operation among players [9] has been studied. Game theory was used for strategic interaction among multiple players who make decisions rationally. Decision makers choose their actions in such a way that they maximize the outcome of the game without co-operation and with co-operation based upon the nature of the strategic game. Components of game theory are shown in Table 1. Game theory has been extensively used in both wireless communication and UAV communication networks.

Table 1. Elements of game theory

Components of Game	Components of UAV-aided Network	Explanation
Players	UAVs/Ground Nodes	Rational entities that try to maximize the output of the game
Actions	Relocation of position, Accessing channel, Intruder detection, Beacon scheduling,	Actions taken by players based on the strategic functionality of the game
Utility/Payoff Function	Performance criteria, e.g., coverage SNR, probability, Intruder, detection rate, throughput, delay	Utility is the reward that players get based on the strategies chosen, according to the objective of the game.

A non-cooperative game has been used in [16] to optimize the UAV's location. Being a non-cooperative approach, each UAV tries to maximize its profit share in terms of the number of mobile nodes served. This approach allows each UAV to reach the same decision for its future location, independent of other UAVs. An energy consumption optimization problem has been proposed by Koulali et al. in [17] with a focus on beacon period scheduling. In a non-cooperative game, UAVs choose beacon schedules and compete for the first successful encounter in order to maximize their reward share. Fully distributed learning allows the UAVs to find their own equilibrium beacon period irrespective of their opponents' strategy. In [18], the authors have proposed a co-operative game theoretical approach for coverage area maximization with minimum power. Based on the coverage probability for each UAV, a payoff was defined that depends on antenna parameters and the altitude of the UAVs. Interference was minimized with a minimum number of UAVs and considering adjustable altitudes based on the requirements for deployment. A single UAV is not able to accomplish the complicated tasks of covering an area, relaying, and providing connectivity. Therefore, for such missions, a need arises to form a coalition describing coverage utility with minimum energy usage [19]. The proposed coalition formation game based on the pareto order ensures the existence of a stable coalition and better performance. Ruan et al. in [20] studied a coverage problem and proposed an energy-efficient coverage model with multi-UAVs describing co-operative behaviour between UAVs in two phases: coverage optimization model and power minimization model. A co-operative game model is formulated with the proof of the Nash equilibrium point of the game. In [21], authors have proposed a Bayesian Stackelberg game for a multi-UAV network considering the anti-jamming transmission problem and also investigated mutual interference among users. An algorithm was designed to obtain a unique Stackelberg equilibrium, and the uniqueness of the equilibrium was proved.

3. System Model

3.1. Problem Formulation

An area with dimensions l*b is considered in which ground users are located in uniform distribution, a group of homogeneous fixed wings Low Altitude Platform (LAP), such as quadcopter UAVs with the same height and power level, having co-ordinates (x_i, y_i, z_i) will provide coverage to this area so that they serve all the ground nodes as shown in Figure 2. UAV-BS are located at an optimal height (h) that results in the largest coverage radius (r) [9]. It has been assumed that there are no obstacles in the environment between UAV-BS and GUs, i.e., direct free space communication.

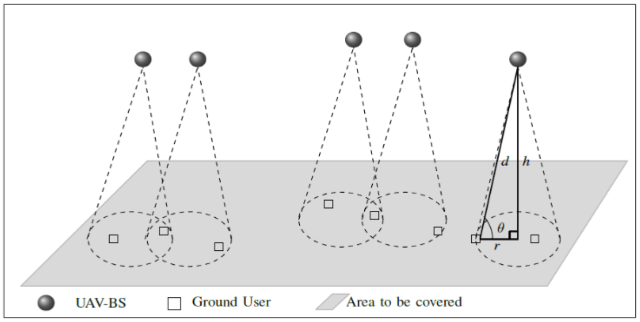

Fig. 2 Network coverage model for UAV-BS

The location of the area to be covered is known to the UAVs, and the location of the UAVs is also passed through the Global Positioning System (GPS) in a real-time environment.

3.2. Radio Frequency Propagation Model

The communication signal between UAV and GU in airborne to ground wireless communication will propagate in two ways [22, 23]: Line of Sight (LoS) or near line of sight and Non-Line of Sight (NLoS) communication. In LoS, a direct communication and signal from the UAV to the GU is established. In NLoS, signals get reflected or diffracted, and that reaches GU. Radio signals from UAV-BS to GU propagate in the space without any obstacles, as shown in Figure 2. Some signal may get scattered because of the surrounding buildings in the area, affecting UAV-GU transmission. This shows free space path loss communication between UAV-GU. It is also assumed that the Doppler shift caused by the mobile UAV is adjusted preferably. The factors associated with UAVs are antenna gain for sensing purposes and path loss. Therefore, ensuring an accurate assessment of the mission's coverage utility is an open issue that must be worth considering. The antenna gain G and beam angle $(\emptyset)$ of UAVs can be evaluated based on [24] as:

$$G = \begin{cases} G_{ml}, & -(\emptyset)/2 \geq \emptyset \leq (\emptyset)/2 \\ \frac{1}{sin^2(3\pi/2\sqrt{N_O})}, & \text{otherwise} \end{cases} \quad (1)$$

Where G_{ml} denotes main-lobe gain for directional antenna, $\frac{1}{sin^2(3\pi/2\sqrt{N_O})}$ corresponds to the side lobe gain and N_o is number of antenna elements in the UAV. Both *LoS* and *NLoS* have their own propagation probabilities, *P(LoS)* and *P(NLoS)*, respectively.

$$P(LoS) = \frac{1}{1+aexp(-b(\frac{180}{\pi}-a))} \quad (2)$$

$$P(NLoS) = 1 - P_{LoS} \quad (3)$$

Where a and b correspond to environmental constants and θ is the elevation angle of GU to the UAV-BS. Here, θ is calculated as $\tan^{-1}\left(\frac{h}{r}\right)$ as in Figure 2.

As reported by [21], UAV-BS coverage probability with respect to GU depends upon many factors such as the location of UAV-BS and GU, environmental factors, path loss, and transmission carrier. Depending on the type of propagation paths between UAV and GU, there will be two types of path loss, i.e., PL_{LoS} and PL_{NLoS} respectively.

$$PL_{LoS} = 20.\log\left(\frac{4.\pi.f_c.d_{ij}}{c}\right) + \eta_{LoS} \quad (4)$$

Where f_c represents the carrier frequency used by UAV's transmitted signals, c is the speed of the signal wave, and d_{ij} is the distance between i^{th} GU and j^{th} UAV-BS is calculated as $\sqrt{r^2 + h^2}$ shown in Figure 2.

$$PL_{NLoS} = 20.\log\left(\frac{4.\pi.f_c.d_{ij}}{c}\right) + \eta_{NLoS} \quad (5)$$

Here, η_{LoS} and η_{NLoS} are average of additional free space path loss is influenced by environmental conditions. Initially, it is unknown whether the link is *LoS* or *NLoS*; therefore, the expected UAV to GU communication path loss (in decibels) is determined as:

$$PL_{db} = P_{LoS} * PL_{LoS} + P_{NLoS} * PL_{NLoS} \quad (6)$$

that is

$$PL_{db} = 20.\log\left(\frac{4.\pi.f_c.d_{ij}}{c}\right) + P_{LoS}(\eta_{LoS} - \eta_{NLoS}) + \eta_{NLoS} \quad (7)$$

If P_{tx} corresponds to the transmitted power level of UAV-BS, then received power P_{rx} will be

$$P_{rx} = P_{tx} - PL_{db} \quad (8)$$

To ensure a stable link between UAV and GU, there must be a threshold power P_{min} such that

$$P_{rx} \geq P_{min} \quad (9)$$

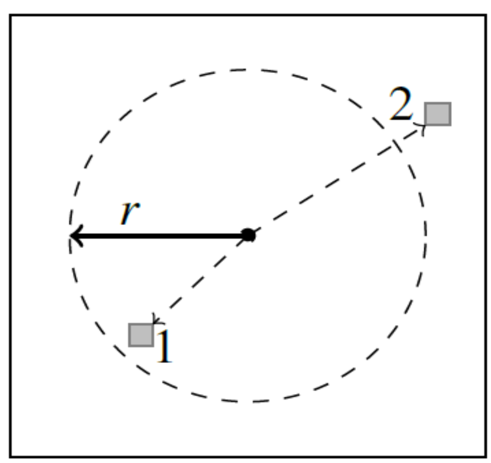

Fig. 3 Distance of UAV-BS from covered and uncovered ground users

P_{min} is the minimum power level needed for reliable reception, and from [6], it is calculated as:

$$P_{min} = 10log(\beta . N + \beta . I) \quad (10)$$

Where β is the Signal-to-Interference and Noise Ratio (SINR), N is the power of the noise signal, and I denotes the mean interference received power from the closest UAV and is given by:

$$I = P_{tx} . \left(\frac{1}{sin^2(\frac{3\pi}{2.\sqrt{N_O}})}\right) . \left(10^{-\left(\frac{\mu_{LoS}}{10}\right)} . P(LoS) + 10^{-\left(\frac{\mu_{NLoS}}{10}\right)} . P(NLoS)\right) . \left(\frac{4.\pi.f_c.dij}{c}\right)^{-m} \quad (11)$$

m is the pathloss exponent and must be ≥ 2.

Pathloss value must also be within a certain limited threshold PL_{thres} such that the communication link will not break.

$$PL_{db} \leq PL_{thres} \quad (12)$$

PL_{thres} indirectly represents the coverage radius of UAV-BS. Within this radius, all the users will be in communication range of UAV-BS as presented in Figure 3. From the above equations of UAV-BS to GU air-to-ground communication, the probability of coverage of j^{th} UAV to i^{th} GU will be calculated according to [6], as follows:

$$Prob_{cov} = P_{LoS,j} * Q\left(\frac{P_{min}+PL_{thres}-P_{tx}-G+\mu_{LoS}}{\sigma_{LoS}}\right) + P_{NLoS,j} * Q\left(\frac{P_{min}+PL_{thres}-P_{tx}-G+\mu_{NLoS}}{\sigma_{NLoS}}\right) \quad (13)$$

Where Q denotes Q-function, (μ_{LoS},σ_{LoS}) and (μ_{NLoS},σ_{NLoS}) represents the mean and variance of the shadow fading for *LoS* and *NLoS* links, respectively. If the UAVs come closer to another UAV, then there will be interference among them; therefore, it should be taken care of that P_{min} should not create interference and maximize the coverage range.

4. Co-Operative Game Theoretic Approach for Coverage Area Maximization

In the previous section, the coverage probability criterion of the UAV was evaluated based on the UAV-to-GU communication link. Now, in this section, a co-operative game theoretical approach is discussed in which the coverage probability function mentioned in Equation (13) will be the utility/payoff function of the game to achieve the objective of maximum coverage.

After that, some assumptions and settings regarding the game will be presented to solve the coverage maximization game under the conditions of minimum power as well as minimum interference requirements for the users in the specified area.

Game theory represents a field in applied mathematics that analyzes and simplifies the interaction among rational players to produce some output in accordance with the utilities/payoffs of players. Game theory is applicable in vast areas like economics, computer science, social science, biology, logic, and many more. A game could be co-operative or non-cooperative based on the nature of the game objective. In a *Co-operative game*, players form groups to take mutual actions for a collective payoff. In a *Non-cooperative game*, players do not form a coalition or group for a collective approach; instead, they play in competition with other players and try to increase their payoff individually.

4.1. Co-operative Coverage Area Maximization Game Description

In this work, the co-operative game theory model is applied to a coverage area maximization scenario. The components of our game include:

4.1.1. Players

Players are the main set of elements of a game that will play the game. UAVs are the players of the proposed game, i.e., *UAVs* = $(UAV_1, UAV_2, UAV_3, \ldots\ldots, UAV_K)$.

4.1.2. Actions

Actions form the strategy set. Players select an action from their available action set for their next movement in the game. In our game, while covering GUs, UAVs have to take two action scenarios to move to the next location, as follows:

Case 1: If GU is located outside the coverage radius r of UAV-BS, then UAV navigates toward the uncovered UAV.

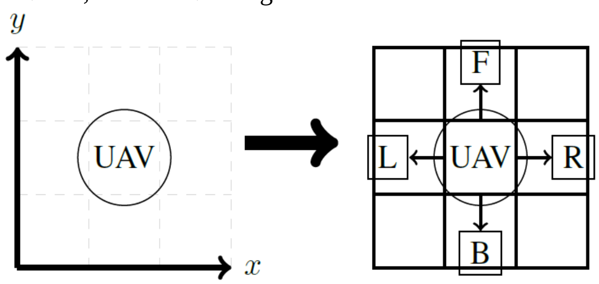

Fig. 4 Next movement of UAV-BS according to the action plan

For every player, there are 5 actions, i.e. $\{Left, Right, Front, Back, Centre\}$ in a 2D scenario. UAVs, while covering GUs, either stay in the center state or current position, or move to any of the other 4 action states as shown in Figure 4 according to their co-operative game plan.

Case 2: A threshold distance d_{Th} as shown in Figure 5, a link is used between two UAVs so that there will not be repeated coverage of a GU in the coverage area. When the spacing between 2 UAVs is smaller than d_{Th}, then UAV shift away from each other; otherwise, there will be no effect. This also ensures the minimum interference among UAVs as well as GUs. Therefore, action 6^{th} will be between two UAVs as:

$$(X_n, Y_n) = (X_o, Y_o) + MaxStep; \quad (14)$$

Where (X_n, Y_n) represents the updated position of UAV, (X_o, Y_o) is the old position of UAV, and MaxStep is the maximum step size that UAV takes to avoid redundant coverage and interference. Each UAV, according to the co-operative game scenario, tries to maximize utility/payoff and, therefore, chooses an action set in the direction of increasing the collective utility function, irrespective of the previous action chosen. Therefore, there are 6 actions in the action set for UAVs, such as A_{UAV_k}=$(A_1, A_2, A_3, A_4, A_5, A_6)$.

4.1.3. Utility/Payoff Function

Utility is the evaluation function for each player to calculate the resulting outcome based on the action set chosen. In the co-operative game, each player covers the mission area according to the chosen action set as discussed above. The utility function is the coverage area covered by the player according to the coverage probability function. Each player co-operatively contributes to maximize the utility/payoff value. Therefore, coverage value, i.e., the utility of the game, is obtained by summation of coverage for all the GUs in the mission area to be covered.

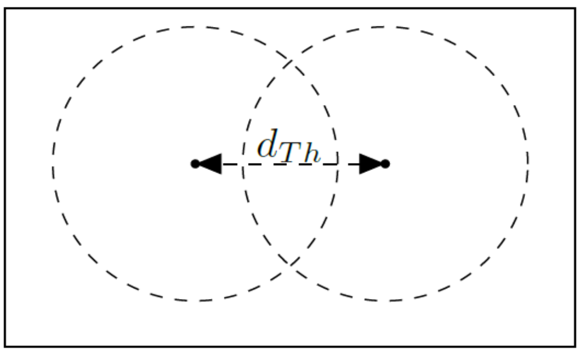

Fig. 5 UAV-UAV overlapping distance

4.2. Game Implementation

In the coverage game, every UAV seeks to optimize its payoff through exploration of new devices in the assigned area. To accomplish this task, each UAV has an action set in the assigned area network. To achieve the maximum coverage, each player selects the action set in accordance with the action set selected by the neighbor player to achieve the Nash equilibrium condition, and that can result in achieving the optimal coverage point. Therefore, the game is analyzed depending on the action set chosen by the players in each iteration. According to [25], the payoff of each player will depend not only on the decision it makes but also on the decision taken by its neighbors. Therefore, the utility function for covering a GU i by any UAV $k\epsilon K$ will be:

$$UF_{i,K}(a_k, a_{J_k}) = \left(1 - \prod_{k\epsilon K} \left(1 - Prob_{cov(i,k)}\right)\right) \quad (15)$$

Where a_k is the action of k^{th} player, J_k Denotes the set of neighbours of k and a_{J_k} is the action set of neighbours of k. The aggregated coverage of the whole assigned area is calculated by the summation of the coverage value/utility of each player, and that aggregated value will represent the payoff of each UAV. Therefore, aggregated coverage will be:

$$U_k = \sum_{i\epsilon R^2} UF_{i,K}(a_k, a_{J_k}) \quad (16)$$

Where R^2 represents the area to be covered in the detection range of UAVs. Then, the optimal coverage will be obtained by optimizing the coverage of the entire assigned network as:

$$P_{cov}: max_{k\epsilon K} \; U_k \quad (17)$$

Each UAV, which is in co-ordination with other neighbor UAVs, i.e., overlapping the GU as shown in Figure 2, forms a coalition and they try to maximize their aggregate coverage utility value. The multi-UAV coverage maximization problem is developed as a co-operative coverage game with Equation (15) as the utility function of the game. The single-step movement of a UAV is determined with respect to the UAV k's position.

4.2.1. Exact Potential Game

Let K be the number of UAVs (players), A is the action set of players with A_{UAV_k} be the action of each player and UF be the utility function, then the game G represented as: $G = (K, A = a_1 * a_2 *.....* a_k, UF = A \to R^N)$ be the exact potential game having the potential function as $\delta: A \to R$ in a way that $\forall k, \forall k_{-1}\epsilon A_{-k}, \forall a'_k, a''_k \epsilon A_k$,

$$\delta(a'_k, a_{-k}) - \delta(a''_k, a_{-k}) = U_k(a'_k, a_{-k}) - U_k(a''_k, a_{-k}) \quad (18)$$

This shows that when a player changes its present state to another, this unilateral deviation is equivalent to the difference in the potential function. An EPG has the property that every potential game gives at least one Nash Equilibrium (NE) [26].

4.2.2. Analysis of Nash Equilibrium

In potential games, a learning algorithm [27] known as Spatial Adaptive Play (SAP) ensures convergence to a pure NE, and with high probability, it optimizes the potential function. The SAP algorithm provides better performance while exploring the coverage area.

According to SAP, one player updates its action randomly, and the remaining players repeat their current actions as $a_{-k}(t+1) = a_{-k}(t)$ where t is the iteration. UAV k chooses a strategy set $a_k \epsilon A_{UAV_k}$ with a probability $prob_k(t)$ and evaluated according to research work [12, 28].

$$prob_k(t) = \frac{e^{\tau * U_k(a_k, a_{-k}(t))}}{\sum_{a_k' \epsilon A_{UAV_k}} e^{\tau * U_k(a_k', a_{-k}(t))}} \tag{19}$$

Where a_{-k} represents all UAV's action set, excluding the action set of k^{th} UAV i.e. UAV_k, a_k' is the set of remaining actions excluding the current action chosen, and τ is the exploration parameter and is greater than zero, i.e., $\tau \geq 0$. According to [29], $\tau = log(1+t)$ and determines that the UAV has to select a suboptimal action. There are conditions for the value of τ, i.e., if $\tau = 0$, then player k selects any of $a_k \epsilon A_{UAV_k}$ with the same probability. For τ, being a small value leads to slow convergence, and a bigger value of τ, the UAV selects the best response with higher probability.

Coverage utility as a potential function is represented as:

$$\delta(a_k, a_{-k}) = \sum_{i \epsilon R^2} UF_{i,K}(a_k, a_{J_k}) \tag{20}$$

Where $U_{i,K}(a_k, a_J) = UF_{i,K}(a_1, a_2, \dots, a_K)$. With this potential function in (20), each player (UAV) operates without knowing the decision chosen by any other UAVs for calculating its payoff value for a particular action chosen. The new movement overlaps with any other UAV, so they consider the new interference distance d_{Th} Otherwise, they fall outside the coverage zone of the neighbouring UAVs. Also, when a UAV locates a GU, it takes into account its coverage value and its neighbouring UAVs, and it does not take the neighbors of neighbors so as to avoid redundancy.

$$\begin{aligned}
\delta(a'_k, a_{-k}) - \delta(a_k, a_{-k}) &= \sum_{i \epsilon R^2} UF_{i,K}(a'_k, a_{-k}) - \sum_{i \epsilon R^2} UF_{i,K}(a_k, a_{-k}) \\
&= \sum_{i \epsilon R^2} \left(\left(1 - \prod_{k \epsilon K} \left(1 - Prob_{cov(i,k)}(a'_k, a_{-k})\right)\right) - \left(1 - \prod_{k \epsilon K} \left(1 - Prob_{cov(i,k)}(a_k, a_{-k})\right)\right) \right) \\
&= \sum_{i \epsilon R^2} \left(\prod_{k \epsilon K} \left(Prob_{cov(i,k)}(a'_k, a_{-k})\right) - \prod_{k \epsilon K} \left(Prob_{cov(i,k)}(a_k, a_{-k})\right) \right) \\
&= \sum_{i \epsilon R^2} \begin{pmatrix} \prod_{k \epsilon K} \left(Prob_{cov(i,k)}(a'_k, a_{-k}) - Prob_{cov(i,k)}(a_k, a_{-k})\right) + \\ \prod_{k \epsilon J_k} \left(Prob_{cov(i,k)}(a_k, a'_{J_k}) - Prob_{cov(i,k)}(a_k, a_{J_k})\right) \\ - \prod_{k \epsilon K \setminus J_k} \left(Prob_{cov(i,k)}(a_k, a'_{J_k}) - Prob_{cov(i,k)}(a_k, a_{J_k})\right) \end{pmatrix}
\end{aligned} \tag{21}$$

Let us suppose that any random UAV k changes its state from a_k to a'_k unilaterally, then the variation in its potential function with respect to unilateral shift will be: according to Equation (21), it is observed that UAV k's action affects only the payoff of its neighbors. $K \setminus J_k$ represents that J_k are excluded from K. Since the action taken by any player k only affects its neighbour's payoff, therefore

$Prob_{cov(i,k)}(a_k, a'_{J_k}) - Prob_{cov(i,k)}(a_k, a_{J_k}) = 0, \forall k \epsilon K \setminus J_k$
Simplifying Equation (21) results in:

$$\delta(a_{k,s1}, a_{-k}) - \delta(a_{k,s2}, a_{-k}) = U_k(a_{k'}, a_{-k}) - U_k(a_k, a_{-k}) \tag{22}$$

From the Equations (18) and (22), it is observed that as UAVs changes their states or actions, their local utility function as well as potential utility function will be same and this proves that the co-operative game can be classified an exact potential game and there will be at least one Nash Equilibrium on unilaterally changing from one state to another as per the criteria of exact potential game. From the above set of equations, it becomes clear that the potential function represents the total coverage utility, which indicates that the current utility of each player is related to the utility of global coverage.

It has been proved that the proposed co-operative coverage problem is an exact potential game. To explore the Nash Equilibrium in the game, a learning algorithm is needed to prevent the strategy selection of players from failing. Therefore, a summarized approach must be presented in the form of an algorithm:

Algorithm 1 explains the SAP-based approach for co-operative game theory with the objective of coverage area maximization. A summarized detail of the proposed work has been presented in this algorithm.

To reduce interference, a distance parameter has been added so that redundant GU are not covered. Initially, a UAV is chosen arbitrarily from the UAV player set, and they approach the nearest GU from their coverage range or within their coverage.

Each–UAV calculates the distance from its neighbor using a distance criterion. If the spacing between two UAVs falls below the threshold d_{Th} then, a MaxStep size will be added to the current UAV-UAV distance to avoid interference and redundant coverage of UAVs. If threshold d_{Th} is in a limit, then UAV checks the distance between UAV and GU.

UAV covers only those GUs that are in its coverage radius range. If a GU will come in its coverage range, then UAV selects the next step according to the SAP probability $prob_k$(t).

Algorithm 1: Co-operative coverage maximization algorithm based on SAP (CCMA-SAP)

1. Input: Initialize the parameters, iteration no., actions, UAV location
2. While: iteration no. $<$ max iteration, do
3. Randomly select a UAV player k ϵ K
4. UAV calculates its threshold distance from neighbor UAVs
5. If threshold distance $< d_{Th}$
6. Update the distance $(X_n, Y_n) = (X_o, Y_o) + MaxStep$
7. else if Distance between UAV and GU $>$ Coverage Radius r
8. Choose action from the action sets (L, R, F, B) according to $prob_k(t) = \frac{e^{\tau * U_k(a_k, a_{-k}(t))}}{\sum_{a_{k'} \epsilon A_{UAV_k}} e^{\tau * U_k(a_{k'}, a_{-k}(t))}}$
9. Calculate U_k for all actions and play based upon $prob_k(t)$ and update its state
10. else Repeat the previous action and stay in the same position
11. Calculate U_k
12. Increase iteration no. by 1
13. End While

For each iteration, UAVs calculate their payoff function co-operatively, including their neighbor's payoff function in a manner that gives the highest utility value for maximizing coverage of GU in the specified area. This update process, after every iteration, converges to a global maximum coverage. Figure 6 presents a detailed flowchart of the designed algorithm. A detailed flowchart of the proposed algorithm is presented in Figure 6.

4.3. Complexity of Algorithm 1

At each iteration, UAV 'k' calculates its distance from other UAVs, therefore O(K^2) computation needed in the worst-case scenario. Every distance update step needs O(1) time, and the UAV calculates its distance from GU 'G' in its coverage in approximately O(G) computations. SAP probability calculations need |K||G| computations. Therefore, overall, the complexity of our CCMA-SAP will be O(|N||K||G|).

5. Simulation and Results Discussion

To evaluate the efficacy of our proposed work, a simulation has been executed with Intel Core i7-1255U, 3.50 GHz P-cores, 16 GB memory, and Windows 10 using Python 3.9 for a co-operative game for UAV-GU communication. For setting up the parameters as described in Section 3, UAV networks from [10, 12, 24] are considered for urban environment without obstacles and parameters are elaborated in Table 2.

In this work, a total of 8 UAVs are deployed randomly at a fixed height h. Total Ground Users (GU) are 50, which are deployed in the mission coverage area of $1000 * 1000m^2$ without obstacles and their locations are known prior to the UAVs, i.e., the area and borders.

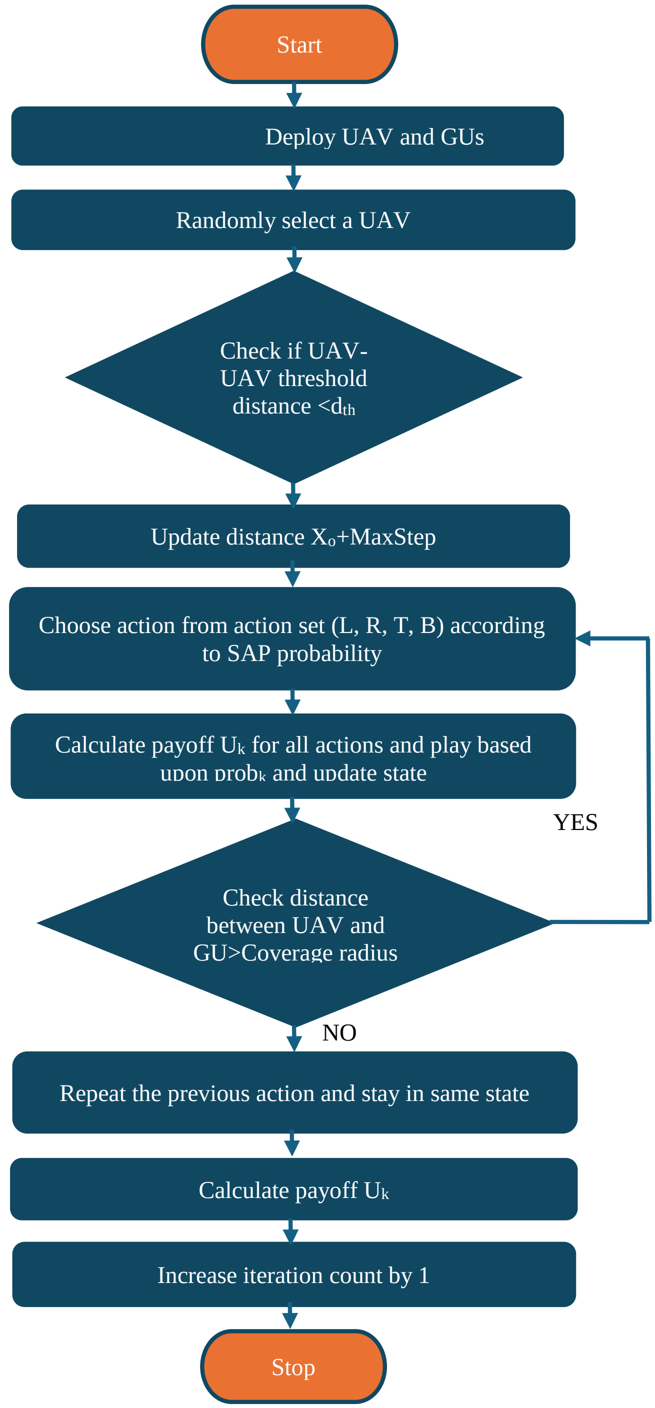

Fig. 6 Flowchart for CCMA-SAP algorithm

5.1. Deployment

For the sake of simplicity, 8 UAVs and 50 GU were chosen to test our work in the specified area. In Figure 7, all the UAVs are randomly deployed at a fixed height in 3D, and their projection is calculated on the ground area. GU is also deployed in the specified area randomly. A large number of GUs are not covered by the projection of UAVs. UAVs calculate the threshold distance d_{th} with their neighbour

UAVs, and if this distance is less than the d_{th} then moves away with a maxstep size so that interference can be reduced, otherwise continue with the game. After covering the GUs in the coverage range, UAVs move to their nearby GUs to cover them according to the action taken by the probability calculation of the SAP approach mentioned above. In this work, 8 UAVs have been used to reduce the interference among UAVs.

5.2. Total Coverage

Total co-operative coverage of UAVs calculated across different UAVs count as $(K = 4,5,6,7,8)$ against the number of iterations at a fixed transmission power level of 35dBm.

Table 2. System parameters

Symbols notation	Description	Values
l*b	Coverage Area	1000*1000 m^2
f_c	Carrier frequency	2 GHz
h	Height of UAVs from the ground	100 m
r	Coverage Radius of UAVs	50 m
N_o	No. of antennas	16
a	Environmental constant	0.6
b	Environmental constant	0.11
c	Speed of light	$3 * 10^8$ m/s
μ_{LoS}	Standard deviation of LoS	1 dB
μ_{NLoS}	Standard deviation of NLoS	20 dB
m	Path loss exponent	2
β	Noise ratio	5
N	Noise power	-120 dB
P_{tx}	Transmission Power	25 to 45 dBm

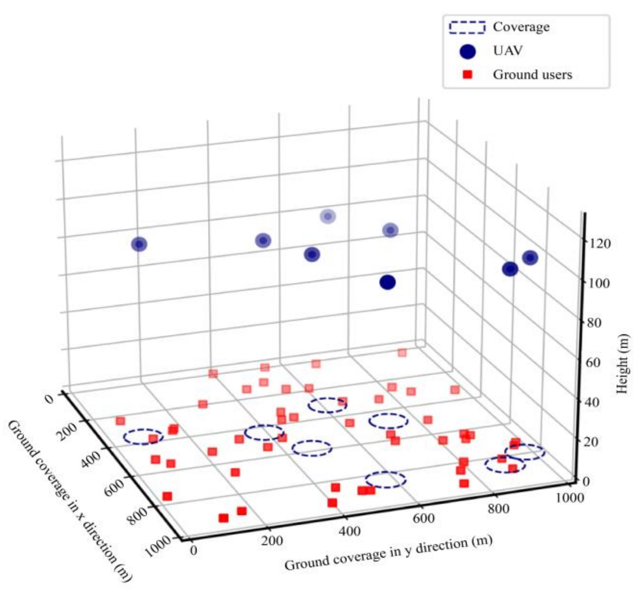

Fig. 7 3D Deployment of UAVs and GUs with UAV projection covering GUs

This is the utility coverage value of the proposed game in which the UAV has two options: play the game and change its state to another state according to the action taken, or stay in the same state and repeat its action if it did not meet the conditions. A threshold coverage is set to 0.5, i.e., if the total coverage lies below this threshold, then the communication need is not met; otherwise, when greater than 0.5, then the communication need is fulfilled. It is observed from Figure 8 that UAVs $(k\epsilon K = 4,5,6)$ did not meet the communication need, and only k = 7 and 8 meet.

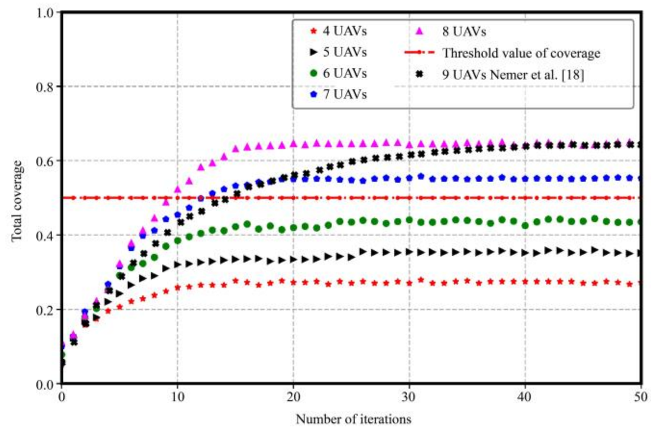

Fig. 8 Total coverage with number of iterations for UAV-to-GU communication for different number of UAVs using the CCMA-SAP algorithm

The deployment scenario is repeated 15 times, and based on those values, average values are taken to ensure the effectiveness of the proposed approach. From Figure 8, it is observed that initially, all the UAVs try to maximize coverage according to the co-operative game objective, and after that, they reach a steady state of maximum coverage value. With an increase in the number of UAVs, the total coverage value increases.

In the present study, an additional parameter (threshold distance, d_{th}) has been used along with the 6 action game strategy to avoid interference among UAVs. The proposed simplified game approach reduced the complexity of choosing the next action based on two different cases. The newly designed algorithm with constraints on coverage radius resulted in achieving maximum coverage for 8 UAVs. While the same coverage was obtained for 9 UAVs by Nemer et al. [18], they used a total of 11 UAVs with a complex game strategy of 27 actions.

In Figure 9, the relation between total coverage is shown with the iterations count for an 8-UAV network at different power levels. With an increase in power level, coverage value increases in accordance with the radio frequency model used. Power levels are taken in accordance with the condition specified in Equation (9), i.e. $(25,30,35,40,45)dBm$. More power level increases interference among UAVs and also affect the network. From the curve, it is observed that with an increase in power, coverage value increases and reaches a steady state, which signifies that maximum coverage has been reached.

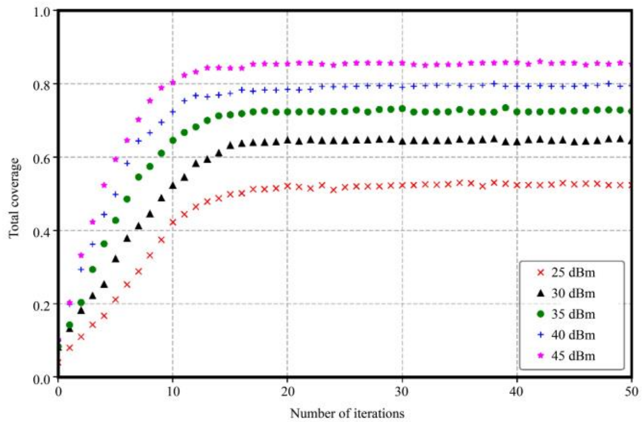

Fig. 9 Total coverage with the number of iterations UAV-to-GU communication for different power levels

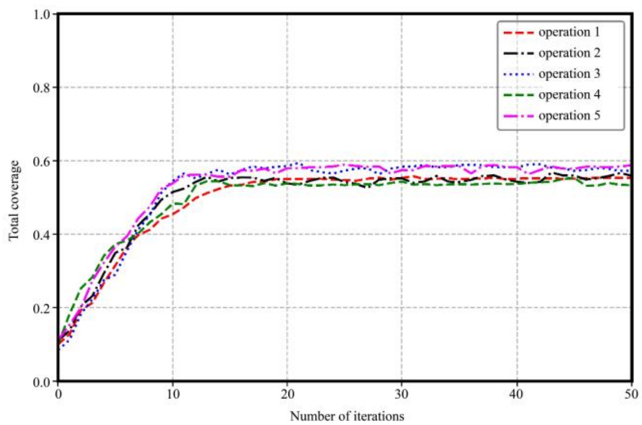

Fig. 10 Convergence of total coverage showing nash equilibrium reached using CCMA-SAP algorithm

5.3. Convergence of Nash Equilibrium

Figure 10 shows the convergence of aggregated coverage as a function of iteration count for an 8-UAV network with a maximum power of 45 dB. The CCMA-SAP algorithm was repeated 5 times to prevent any uncertainty. Every time, the curve follows the coverage greater than 0.5, and after a particular number of iterations, it reaches a steady state. The coverage value do not deviate from its convergence value. In a co-operative game, every player is aware of the strategy used by other players. Therefore, the strategy of every player is optimal while considering the strategies of other players. Each player achieves the same outcome without deviating from its strategy. In our approach, from Figure 10, it is clear that in every operation, without deviating, the coverage value reaches approximately a certain value of convergence.

This convergence results in the Nash equilibrium point of the game, which signifies that the system has a fixed point at which no deviation occurs. Convergence proves that the proposed co-operative game has at least one Nash Equilibrium.

5.4. Game Theory vs Non-Game Theory

Game theory finds widespread application in wireless communication, all thanks to advances in technology. Game theory has been used to facilitate strategic interaction among players to make rational decisions. A single UAV will not be able to work as efficiently as multiple UAVs. Multiple players create a complex network, and the need arises to have co-operation among them. Therefore, co-operative game theory has been discussed in Section 4.

Now, we compare the proposed work with a non-game theoretical approach [30] based on area partitioning of the sensed space. This approach focuses on the objective of coverage area maximization using altitude and sector angle of the UAV as the main variables. Downward-facing cameras are used to accomplish area coverage. Every agent has been given a responsibility for a particular cell on the basis of the sensed region and a constant coverage quality over these cells. Mobile agents communicate indirectly with their neighbours in multiple hops, resulting in collaborative coverage of the particular region of interest. In this approach, UAVs {K=4,5,6,7,8} are distributed randomly in a region 1000*1000 m^2. Other parameters are the same as mentioned in Table 2. The angle of the camera is tilted such that it reaches 45^o. The simulation results are shown in Figure 11. In a non-game theoretic approach, demonstrating coverage area with respect to iteration count is required to accomplish the optimal coverage. Each UAV tries to minimize interference with neighbouring UAVs and maximize coverage by adjusting its location to meet the coverage quality. They try to capture maximum coverage by covering their assigned cell within their altitude and sensing radius. It is observed that coverage of 4, 5, and 6 UAVs falls below the acceptable value of 0.5, i.e., the threshold value. 7 and 8 UAVs have coverage above 0.5, which is acceptable.

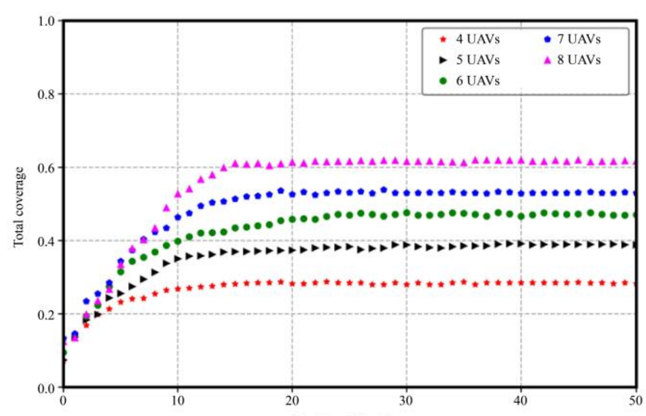

Fig. 11 Total coverage with number of iterations for UAV-to-GU communication for different number of UAVs using non-game theory

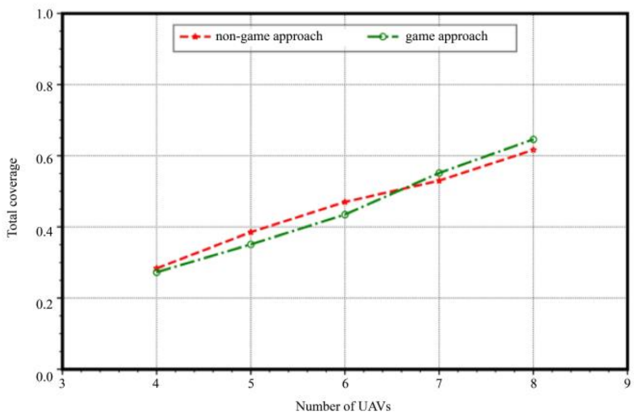

Fig. 12 Comparison of total coverage with UAVs count using game theory and non-game theory

The curve shows that coverage increases sharply initially and then becomes almost constant with an increase in iterations. Initially, there is a large gap between consecutive coverage values, and as we go above, the gap reduces if we compare it to Figure 8.

Figure 12 shows the comparison of two approaches: the suggested approach, considering game theory, and the corresponding non-game theoretic approach. This shows the relation between coverage obtained and the number of UAVs. For acceptable coverage with 7 and 8 UAVs, both the proposed game theoretic approach and the alternative non-game theoretical approach result in acceptable coverage values, i.e., above 0.5.

It is clear from the curve obtained that below a 0.5 value of coverage, the non-game theoretical approach performs better, but after 6 UAVs, the game theoretical approach outperforms, and the coverage value increases.

6. Conclusion and Future Work

In this article, a co-operative game-theoretic approach is designed for coverage area maximization for UAV-GU wireless communication. This is a multi-UAV game approach based on the selection of the next movement. A power threshold Radio frequency propagation model has been adopted to calculate the coverage probability with LoS and NLoS links in the UAV to GU downlink communication scenario. A mathematical model for the game has been proposed. A UAV-UAV relative distance parameter has been added to minimize the interference among UAVs. Each UAV tries to maximize coverage utility value, which is a function of coverage probability along with neighbor UAVs, Co-operatively. Proposed game theory with SAP-based probability approach results in optimized coverage and convergence against specified test conditions. The proposed model also has at least one Nash Equilibrium (NE) condition, showing the efficiency of this approach in achieving optimized coverage with minimum threshold power. On comparison of the proposed game theoretical approach with previous work and non-game theoretic approaches, our game approach outperforms.

In the future, obstacles can be added to the game scenario, and work can be extended to include other resource parameters, such as energy, handover, quality of service, etc.

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