Transportation Research Part A 140 (2020) 215–230

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

A game theoretic approach of deployment a multiple UAVs for optimal coverage

Ibrahim A. Nemer*, Tarek R. Sheltami, Ashraf S. Mahmoud

Computer Engineering Department, King Fahd University of Petroleum & Minerals, Dhahran 31261, Saudi Arabia

ARTICLE INFO

Keywords:
UAV networks
Intelligent transport systems
Line of sight
Potential games
Nash equilibrium
Optimal coverage

ABSTRACT

In this paper, a game-theoretical autonomous decision-making approach for efficient deployment of unmanned aerial vehicles (UAVs) in a multi-level and multi-dimensional assisted network is analyzed. The UAVs have directional antennas that work as wireless stations, which provide the best coverage for multiple ground mobile/fixed users. In general, UAVs work in a cooperative manner for achieving the suitable deployment with the optimal coverage values for the candidate region. In this paper, a game theory concept is used and the payoff function for each UAV is defined based on the coverage probability value, which depends on the altitude and the characteristic of antennas in the UAVs. We introduce a mathematical formulation for evaluating the payoff values based on a set of actions for each UAV, and the Nash equilibrium for this kind of game. This approach works in an intelligent way based on the interactions between the UAVs and their neighbors in a connected network and it might work even in harsh environments. In order to minimize interference, the UAVs' altitudes are adjusted based on the antennas and other deployment requirements (i.e. search and surveillance purposes) by using the minimum number of UAVs to cover the candidate geographical region. The simulation results show that the proposed approach achieves the maximum coverage value, converges fast with the environmental changes based on the power levels, and robust for failure scenarios. Finally, we compare our approach against one of the traditional approaches called Collaborative Visual Area Coverage Approach (CVACA) based on uniform coverage quality. The simulation results show that the game approach outperforms the traditional approach in term of the coverage value and the computational time.

1. Introduction

Intelligent transport systems (ITSs) represent the main building block of any smart city (Xiong et al., 2012). Actually, information and communication technologies (ICT) are one of the bases of the road infrastructures for the last decades. Researchers are finalizing the last stage of the next generation of ITS technologies especially connected and autonomous vehicles for large scale worldwide deployment. However, the testing of these technologies on the main roads has already started in so many countries, and serious researches and efforts are still under processing to adjust and regulate these near-future technologies. As the number of interconnected and autonomous vehicles in streets rises, so many new applications and services are needed in order to simplify the human life and make the city as a smart city.

The smartness measurement of any smart city is something related to its healthcare, disaster management, public safety, quality of

* Corresponding author.
E-mail address: inemer@kfupm.edu.sa (I.A. Nemer).

https://doi.org/10.1016/j.tra.2020.08.004
Received 28 December 2019; Received in revised form 3 August 2020; Accepted 11 August 2020
Available online 08 September 2020
0965-8564/

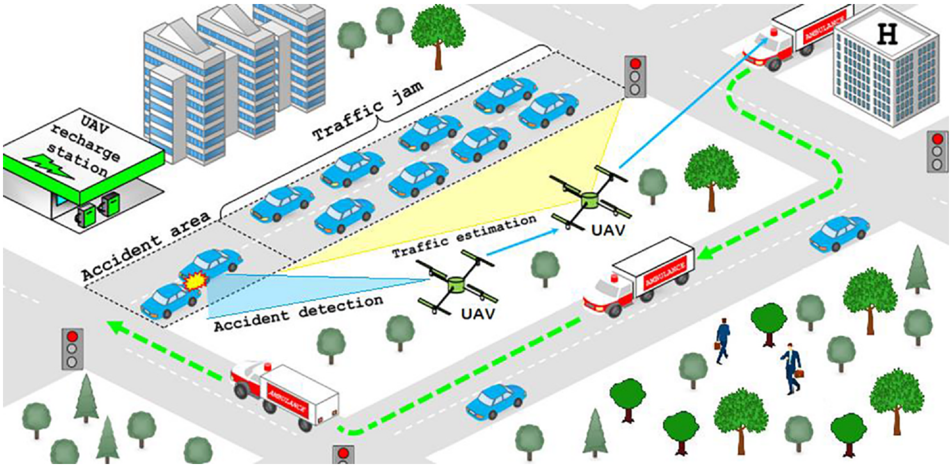

Fig. 1. Collaboration of UAVs for traffic monitoring of a smart city.

life, environmental sides (i.e. traffic monitoring, air quality, energy consumption), and other services. Thus, modern ICTs, robotics, and Artificial Intelligence (AI) consider as essential roles to make cities smarter. These technologies aim to achieve a better infrastructure for the targeted cities as well the needed smart services to reach the best response. The provision of achieving a good infrastructure and lowering the cost of services while distributing some services and facilities everywhere is an important aspect in the smart cities.

More recently, drones or UAVs represent the main technology that makes the city smarter, it is impossible to imagine a smart city without the ITS functional UAV services (Mohammed et al., 2014). UAVs are autonomous devices that travel in the sky and are wirelessly connected with the main infrastructure to serve different applications. UAVs can also work as an aerial base station to transfer communication services (downlink and uplink) for subscribers on the land. Moreover, Line of Sight (LoS) and agility are the main specifications of UAVs that play a vital role in the IoT framework. Automation of the whole transportation system cannot be guaranteed by only automating the vehicles, but other parts of the end-to-end transportation system and the road (i.e. road surveys, support team, traffic police, and rescue teams) also require to be automated. Automation of these parts can be guaranteed by using smart and reliable UAVs, as illustrated in Fig. 1.

Many benefits can be gained by using UAV-assisted networks such as, less line of sight effects compared with the fixed and mobile ground nodes. UAVs has the ability to move in the sky in any direction and it has a flexible deployment, which is required for good coverage and communications. Furthermore, UAV can be used as a relay or a base station node in order to improve the performance of the existing wireless sensor networks and mobile ad-hoc networks (Bekmezci et al., 2013). On the other hand, and despite of these benefits, using UAV-assisted networks comes with some challenges such as; 3D placement of UAVs, energy constrains, collision avoidance, security, path planning and other designing issues (Mozaffari et al., 2015; Orfanus et al., 2016).

The deployment problem, in coverage and tracking purposes, particularly has a high impact on the UAV's energy and it might cause interferences with other neighboring UAVs in both centralized and distributed networks. This requires a suitable approach to address and solve these issues. Many non-game theoretic techniques were proposed for communications between UAVs. Each UAV needs to decide and take a suitable action in a timely fashion maximizing the coverage area and using the minimum power requirements. However, most of these techniques require a fixed communication exchange between the main central unit and other UAVs, so the communication overhead is increased, which is directly proportional to energy consumption. Usually UAVs need to have a self-organizing behavior due to the need of control and simple management with respect to the mobility model.

Game theory simplifies the coverage problem and easy to understand and analyze comparing against other traditional approaches that are required so many constrains to be solved, such as optimization approaches. Moreover, due to the environmental changes and rational behaviors in the UAV-assisted networks, game theory is widely used for solving various problems in the UAV networks (i.e. coverage, task allocation and path planning) (Semasinghe et al., 2017; Saad et al., 2009). The game theory consists from a set of strategies and each player interacts with other players in either a competitive or cooperative way, and any problem can be represented as a mathematical model. Hence, efficient and robust distributed approaches can be implemented to tackle the technical challenges in the UAVs network (Semasinghe et al., 2017). Accordingly, these approaches try to reduce the communication overhead and achieve a good coverage with a minimum energy. Based on UAV's characteristic, game theory is considered as the best tool to fulfill the design requirements and make it more intelligent than traditional approaches.

In this work, we propose a decision-making approach based on the potential games. The coverage and power problem in the UAV-assisted networks is implemented as a potential game for achieving maximum coverage with less power requirements. The reminder of this paper is organized as follows: the related works is presented in Section 2. Next, the problem setup and network model is introduced in Section 3. Then, the proposed potential game approach for optimal coverage is presented in Section 4. After that, the performance analysis for the simulation experiments is discussed in Section 5. Finally, we conclude the main results and make some recommendation for the future works.

2. Background and related work

2.1. Coverage problem in UAVs assisted networks

The coverage path planning problem in the UAVs assisted networks is widely discussed in previous works in term of finding the optimal coverage using traditional techniques. In this subsection, we present some of the recent approaches for finding the optimal coverage with less energy requirements.

Balampanis et al. in (Balampanis et al., 2017) proposed an approach to tackle the cell decomposition and partitioning challenges for a group of heterogeneous UAVs, which use sensors on-board with a specific sensing radius for coverage purposes. These sensors are mainly used to achieve the partitioning process by using a rising regions technique to get an isotropic partitioning with respect to the initial UAVs' positions and their capabilities. After that, they used two techniques to calculate the new change of the partitioning process; this mainly solve the deadlock cases that can occurred within the sensing regions achieving maximum coverage. This approach requires the availability of on-board sensors and using some of the area decomposition and partition techniques for a heterogeneous UAVs network, these techniques increase the computational time for achieving better coverage. Hence, the complexity of the approach is increased accordingly.

In paper (Papatheodorou et al., 1612); Papatheodorou et al. solved area coverage problem for a set of UAVs by using a combined coverage quality metric. UAVs are equipped with a downward facing camera (directional antenna), which covers all ground users that are in the sensing range. Both the covered region and the coverage quality depend on the altitude of these UAVs. Authors used a partitioning algorithm and developed a new gradient based on control law that restricts the adjustment in UAVs' altitudes in order to cover the candidate region. This control law achieved a locally optimal configuration for the whole network based on the combined coverage-quality algorithm, while UAVs are moving in a predefined range of altitudes for the candidate region. This approach is based on the kinodynamics of the UAV, sensing performance, and altitude constrains in order to apply the control law and achieve the optimal coverage. According to these requirements, the complexity and the computational time of the approach are high.

Messous et al. in paper (Messous et al., 2016) studied a network with a fleet of interconnected UAVs and developed a distributed mobility model for the region exploration tasks. UAVs need to optimally scan the candidate region and keeping their connections with neighbors and base stations by using their wireless ad-hoc capabilities. The decision criterion along with the network connectivity and the covered region are based on the residual energy level in the UAVs. Hence, based on the decision and information that was received from the neighboring UAVs, the next movement of each UAV in the fleet decides accordingly. The scheme depends on the wireless ad-hoc capabilities of the UAVs as well as the connectivity between them for achieving the coverage task. Therefore, the overall performance depends directly on the type of the UAV and its wireless capabilities. This will add some constrains on the deployed UAVs based on their specifications.

In paper (Cabreira et al., 2018); Cabreira et al. presented a new energy-aware coverage path planning technique for specific photogrammetric applications. This technique issues paths with respect to the overlapping rates and the image resolution based on the specifications of the camera and its view in order to do a complete region mapping. This model uses a set of optimal speeds for each portion of the targeted path to minimize the consumption energy. Furthermore, the energy model has the ability to predict the overall cost in spiral path to cover the targeted region taking in to account the tuning angle and the entrance speed to achieve more precise system. This approach uses the back-and-forth and spiral algorithms for achieving better coverage in the photogrammetric applications with respect to the energy constrains of the UAVs. The coverage value is low and the computational time is high compared with the previous techniques. Nonetheless, it needs lower energy requirements than that of the previous schemes.

Another coverage path planning approach was proposed by Di Franco and Buttazzo in (Di Franco and Buttazzo, 2016, 2015), where energy and image resolution are the main constrains. The energy model was derived from some real measurements to evaluate the targeted speed under minimum energy consumption values for a specific path. Once the path is defined, then it is possible to derive the speed with respect to the energy constrain. Moreover, a feasibility test has been suggested to check whether the remaining energy is enough to explore the candidate region and is enough for UAV to go back to its starting point. Both approaches depend on finding the optimal speeds for each path by exploring and testing the candidate region. Both approaches are energy efficient but they need long time to find the required speeds.

A solution for the issue of the minimum required time coverage has been presented by Avellar et al. in (Avellar et al., 2015) for a specific region using set of UAVs equipped with image sensors. This method divides into two steps: first, the mission modelled as a graph with a predefined vertices based on specific coordinates for each UAV to cover a region with minimum time, and then a mixed integer linear programming was formulated based on the graph parameters, to route the fleet of UAVs over the candidate region. Moreover, the number of used UAVs to cover that region is specified by solving an optimization problem. It is a complex approach compared with the previous techniques since it has to do two tasks in order to cover the region, this increases the needed time to reach the optimal coverage.

Mozaffari et al. in (Mozaffari et al., 2016) proposed an efficient deployment approach that considers the UAVs as a wireless base stations to provide better coverage for the ground users. The download coverage probability of the UAVs is defined as a function of the antenna gain and the UAV's height. Moreover, authors used the circle parking theory, and calculated the 3D UAVs positions achieving maximum coverage for the whole region as well maximizing the UAVs' lifetime. However, UAV's height should be defined based on the coverage requirements and the beamwidth of the directional antenna in order to avoid the interference issue. In paper (Alzenad et al., 2017); Alzenad et al. proposed an optimal 3D placement approach for UAV base stations in order to increase the number of covered users with a minimum transmission power. They divided the deployment problem into a horizontal and vertical dimensions achieving same optimality. The horizontal dimension represented as a circle placement problem. Both approaches are not intelligent, nonetheless, they achieve better coverage values compared with other approaches, however, they need more time to reach the optimal values.

From the above discussion and due to the UAV's characteristic, flexibility, mobility and LoS ability of the UAV assisted network, these approaches are not suitable for the distributed networks especially when the network is large and dynamically changes with time. Consequently, this force us to look for another tool to achieve the design requirements and make it more intelligent, efficient and robust distributed network than other existing approaches.

2.2. Games theory in UAVs assisted networks

Game theory has been used widely in designing and solving communication problems in the wireless network as well in the UAVs assisted networks. In this subsection, we do a survey for the recent researches that used game theory concept for solving some of UAVs challenges.

A potential game approach was proposed by Choi and Lee in (Choi and Lee, 2015) for distributed cooperative informative sensors, where the main purpose here is to raise the shared information between the quantities of interest and the measurement parameters. They showed that the local utility can be defined by a conditional shared information for the UAV with respect to other UAVs, which directs to a game with a global utility based on the original common information for the cooperative problem. After that, they applied this joint game approach to achieve a distributed behavior that mainly converges to a pure Nash equilibrium. It is an intelligent game approach and it is used to maximize the shared information between the quantities of interest and the measurement parameters, however, this kind of games is not suitable for solving the coverage problem.

Saad et al. in (Saad et al., 2009) proposed a hedonic coalition formation game between UAVs and their missions in order to visualize the task allocation issue and forming a disjoint coalition. Each of the constructed coalition is mapped to a polling system; this system includes a set of UAVs that interact with each other for collecting packets from different number of tasks. UAVs has the ability to work as collectors or relays in the system. Moreover, authors proposed another approach for forming the coalitions; it allows UAVs/tasks to join or leave the coalition based on their throughput and the coalition delays. Another hedonic game decision making technique was proposed by Jang et al. in (Jang et al., 2018) to tackle the task allocation issue for a swarm of UAVs. They considered the cooperation of self-interested UAVs and they showed that the technique is converged to a Nash stable partition in a specific polynomial time. It is simple and working based on the local interactions with the neighboring UAVs under asynchronous environments and connected network. Both approaches were used to solve the task allocation problem in the UAVs network not the coverage problem, however, the hedonic game needs more time to reach the Nash equilibrium point for all UAVs.

This paper (Roldán et al., 2018) showed that the UAVs can compete or cooperate in order to achieve a certain task. Roldán et al. designed two algorithms one competitive and other one is cooperative, developed and tested multiple scenarios. Their results showed that the cooperative algorithms allocated high number of tasks comparing with the completive algorithm. On the other hand, the competitive one achieved higher value of social utility. Asl et al. in (Asl et al., 2014) proposed a game theoretic approach to evaluate the threshold, which is required to decide the best strategy. They studied this threshold based on the UAVs' utilities and the services' characteristics over multiple strategies. Both researches clarified the cooperative and competitive games as a set of examples and they decide which game is the best based on the specification of the UAVs network.

The problem of optimum beaconing in drone small cell networks with two competing UAVs was explored by Koulali et al. in (Koulali et al., 2016) using a non-cooperative game. In order to achieve the optimum device performance in terms of energy efficiency and encounter rate, authors carefully set the length of periodic beaconing cycles. First, a game theory approach was applied to beacon independent time duration preference. Second, they explored the nature and significance of the Nash equilibrium depending on the sub-modularity game. Next, they developed a distributed learning system that would allow the UAVs to explore their equilibrium for the beaconing period. Eventually, they investigated the feasibility of this beaconing approach by a detailed analytical model. Here, the drone small cells used in this game to extend the wireless communications coverage based on the central authority. Therefore, it is not suitable for all kind of UAVs network and may not hit the Nash level for the distributed networks.

Another game (Charlesworth, 2013) used the required timestamps from the mobile nodes and UAVs to figure out the main strategies as well their payoffs. Hence, the reduction in the information exchanges requires to coordinate between UAVs in order to achieve the same solution for the UAVs with high autonomy and minimal coordination. However, using the usual positioning techniques for more coverage gives the technique more tolerance for missing or delaying the messages exchange. They showed that the competing process between two UAVs achieves a better coverage than that with a single circling UAV and distributing the power between them improves the efficiency of the whole system. Same author published another paper (Charlesworth, 2014), he mentioned that the non-cooperative game allows UAVs to decide about their next movements without the need of any central planning UAV. Both approaches are based on non-cooperative games and suitable for fixed rotor UAVs in a small network.

Li and Duan in (Li and Duan, 2017) proposed a cooperative game of multiple UAVs for search and surveillance purposes. Actually, this game composed from three tasks: coordination UAV motion, sensing observation, and cooperative data fusion. The first task was implemented using a constrained action sets in multi-player potential game. After that, they used a binary log-linear learning algorithm for controlling the UAV motion in order to achieve the optimal coverage. The coordination of other UAVs motion was done by constructing a probability map using a consensus based fusion technique. Based on these stages, the complexity and computational time for achieving the optimal coverage is high compared with other games.

The coverage problem was discussed and implemented in (Ruan et al., 2018) using a coalition formation game (CFG), it has a table partition with a Pareto order. It is mainly composed of the coverage deployment and the coalition selection processes; each UAV has the ability to decide its strategy in a cooperative way in order to improve the overall coverage. This game achieves a good coverage value but it basically depends on a centralized UAV and it contains more than one stage. A comparative study was done in (Anicho et al., 2019) between Swarm Intelligence (SI) and Reinforcement Learning (RL) algorithms in order to find the optimal coordination for better coverage. The RL achieved better overall coverage with the unpredictable dips, whereas the SI showed better stability and faster convergence rate comparing with the RL with less covered regions. Both approaches achieve an acceptable coverage value with minimum requirements, however, it is complex.

Another comparative study between two techniques was done by Giagkos et al. in (Giagkos et al., 2016). The first technique is based on non-cooperative game for finding the next flying actions of the UAVs in a group. The second one uses an evolutionary game to improve the flying maneuvers in a cooperative way. They found that the UAVs in non-cooperative game flied in a balanced and conservative way using the evolutionary game achieved a global solution for the coverage problem in less time by enabling the existing of a predefined flying behaviors for each UAV in the group. The authors compare between a non-cooperative game and evolutionary game, both games need more time to cover the candidate region compared with other games.

Fang et al. in (Fang et al., 2018) evaluated the UAV-assisted networks by using a new metric composed of the transmission overhead and the ratio users' probability. They formulated the problem as a UAV-assisted caching game, and they found the Nash equilibrium of this game by adopting a new log-linear caching technique. Mkiramweni and Yang in (Mkiramweni and Yang, 2018) proposed a new architecture based on the Nash bargaining game (NBG) and they defined the Nash solution beaconing periods for the UAV base stations. NBG allows UAVs base stations to optimize the consumption energy increasing the number of covered ground mobile users. Both approaches are not simple and need long computations but they achieve better coverage values with respect to other approaches.

A game theoretic approach was proposed by Ruan et al. in (Ruan et al., 2018), the approach achieved better coverage based on the energy constrains. This approach is divided into two game problems: coverage problem and power control problem. Both problems have an exact Nash equilibrium points. This energy-aware coverage approach is based on the spatial adaptive play; it is an adaptive game that uses to maximize the coverage and adjust the required power in one level. In this game, UAVs are distributed at the same level and they change their sector angles and sensing radiuses to achieve the best utility values.

In paper (Giagkos et al., 2014); Giagkos et al. proposed a coordination approach for a set of aerial vehicles that used to construct a communication backbone in order to connect the ground vehicles in ad-hoc and highly dynamic manner. This an evolutionary game optimized two main objectives by maximizing overall coverage and minimizing the energy consumption of a good communication network. However, the altitude depends on the required energy for achieving better link quality. This approach is based on the evolutionary game and it is suitable for fixed rotor UAVs. It needs a long time to achieve the optimal coverage due to the construction of the backbone network.

Sharma et al. of (Sharma et al., 2017) presented an intelligent approach for a precise and efficient placement of UAVs based on the candidate region in order to raise the capacity and coverage of the whole network. This approach is composed of a cooperative UAV allocation problem and a Macro Base Station decision stage. They used the entropy and priority-wise dominance algorithms for solving both problems and achieving efficient approach. It depends on the utilization of the entropy for the network formation to specify the UAV controller and do a network bargaining in order to improve the overall throughput, capacity and reduce errors in the mapping process as well decreasing the network delays. This approach depends on a base station (centralized approach) for achieving the optimal coverage. Hence, this is not suitable for any distributed UAVs network and it might suffer from the environmental changes.

Ni et al. in (Ni et al., 2020) formulated the cooperative search problem as a potential game, and they employed the binary log linear learning (BLLL) method to solve the coverage problem in the multi UAVs network. The main goal of this research is to find an efficient method for solving the search area covering and the collaborative control issues in the UAVs network. They used a modified version of the strategy selection technique of game players based on maximizing the utility function. Since, this will make the convergence of the system to the Nash Equilibrium point faster. Moreover, they built a modified action selection strategy using the neighborhood information sharing technique in order to force UAVs' movement away from the zero utility locations. This proposed game showed its effectiveness and feasibility using different set of experiments. However, this game is applicable only for simple environment that does not include any moving obstacles.

A new approach in (Li et al., 1907) is presented, it combines the non-cooperative game concept and the binary log-linear technique (BLLA) in order to find the Nash equilibrium (NE) solution, where the optimal and efficient deployment can be reached using this NE point. Li et al. proposed a synchronous payoff-based binary log-linear learning algorithm (SPBLLA) that uses the learning rate parameter effectively and faster comparing with the traditional asynchronous learning algorithm (PBLLA) in highly dynamic scenarios. So that, this algorithm is more suitable and favorable for highly dynamic and large scale network. However, it is applicable for a specific number of UAVs.

In this paper (Arani et al., 2003), a three dimensional space deployment of UAVs supporting the terrestrial cell networks has been proposed by Arani et al. in the downlink based on a learning approach. This approach is based on a non-cooperative game in the form of satisfaction that basically applied at the level of UAVs. They used a low-complexity approach to solve the game, in which unsatisfied UAVs change their positions based on a learning approach. The simulation results revealed that the proposed learning-based approach dramatically increased the efficiency of the network and decreased the necessary number of UAVs for an unspecified goal benefit.

In paper (Sawadsitang et al., 2020); Sawadsitang et al. presented a Bayesian Shipper Cooperation in Stochastic Drone Delivery (BCoSDD) approach for a specific scenario, where multiple shippers can collaborate to decrease the delivery cost. The approach consists of three main tasks, i.e. package assignment, the establishment of shipper collaboration and cost of the control. Uncertainties of drone failure and abusive behavior of cooperative shippers in this approach are taken into consideration by employing a multi-stage stochastic programming optimization and complex Bayesian coalition game. Detailed BCoSDD experiments were carried out to verify this approach using two datasets, i.e. one from Singapore logistics industry and the second is Solomon Benchmark suite. BCoSDD approach considered as the best solution in term of the cost with respect to other traditional approaches.

Handouf and Sabir in (Handouf and Sabir, 2019), proposed a duopoly framework based on non-cooperative game. Where a specific number of mobile UAVs are moving based on homogeneous Poisson Point Processes (PPP) for serving number of internet of things devices on the ground. The movements of the mobile UAVs are based on Random Way Point (RWP) model. Authors derived the coverage and the service probability functions for each UAV in the network. The Nash equilibrium analysis has been presented based on energy efficiency and pricing policy in order to maximize the system performance. They also introduced a learning scheme that uses the best solution dynamics, which helps operators to easily, reliably and distributive know their joint price-availability strategies. The simulation results showed that this approach maximized the monetary revenues of the UAV's service providers while optimizing the energy consumption. This approach depends only on the homogeneous mobility motions not the heterogeneous ones.

The goal of the paper (Xu et al., 2019) is to resolve a difficult problem that any user may misreport his position or be selfish to adjust the optimal position of the network to be closer to himself. Xu et al. used game theory concept in the proposed approach to specify the final position of a UAV in three dimensional space, by guaranteeing the truthfulness of all selfish users to submit their positions for learning purposes. Moreover, they used strategyproof techniques with specific approximation values, when comparing to the social equilibrium point in order to decrease the social service cost for this placement game. This approach basically works based on a predefined strategyproof technique not applicable for the randomized strategyproof.

In this paper (Garmani et al., 2019); Garmani et al. proposed a new approach in the UAVs network for covering the accesses to the network resources within a specific region with a parameterization with respect to the access price, availability, and quality of service. This problem modelled using non-cooperative game and the strategies are defined with respect to the beaconing, access price, quality of service, and availability. The Nash Equilibrium (NE) point exists and unique for this model and according to this, an iterative algorithm was proposed to calculate the NE in a distributed manner. This approach is restricted for a small set of players since it is based on non-cooperative game.

2.3. Main contributions

Based on the achievements and challenges that has been mentioned in the previous section, we propose a distributed approach for the UAVs assisted networks that implements the deployment and cooperative search problem as a potential game in three dimensions and multi-levels. The proposed approach has a self-organized behavior, where each UAV make its own decisions based on the local and global policies; unlike other non-game and game approaches mentioned in the related work section, which primarily focused on implementing the UAVs decision-making approaches using a central unit or solving the deployment problem by using optimization algorithms for one level or in two dimension with a fixed UAV's altitude.

Our proposed approach uses the same specification of the RF model in (Mozaffari et al., 2016) and we utilize it to achieve the best probability coverage value. However, authors in this paper achieved the maximum probability coverage value by solving an optimization problem with respect to the number of deployed UAVs, power transmission, sensing radius, and the sector angle. Another approach (Ruan et al., 2018) was adopted the same RF model as well and used the game theory concept in order to achieve the best coverage. They considered the probability coverage utility function of the game, the altitudes are fixed and same for all UAVs (at one level). They adjusted the view angle and the sensing radius for achieving best utility value for the whole network. Whereas, the UAVs in our approach are distributed at different levels and they can move in any direction not only in the horizontal direction. Moreover, the set of actions that we use it in our approach are different from the ones that used in (Mozaffari et al., 2016) and (Ruan et al., 2018).

This learning approach is adapted to achieve the optimal coverage in the UAVs assisted networks. Moreover, an appropriate practical values regarding the communication capabilities are used for simulating this approach to be more realistic and efficient. This approach can work in any urban environments, dynamic changes and weather changes. The UAVs are equipped with a directional antennas and suitable observation units. In our game, UAVs represent the players and the next movement in three dimensional space represents the set of actions for each UAV. Each player tries to achieve the best coverage based on its neighbors and the selected action. From the above description, our main contributions in this paper are as follows:

1. UAV to ground communication is presented according to a specific radio model.
2. Game theoretic approach is introduced for multi levels and multi-dimensional UAVs assisted networks based on a potential game. This game tries to achieve an optimal coverage value with less transmission power.
3. We prove that there is a solution (Nash equilibrium point) for this game and it can be found based on the convergence state of the proposed approach.

This paper aims to introduce the readers on how to solve such technical problem in the UAV assisted networks in terms of their characteristics, challenges and benefits for achieving the best coverage with minimum requirements.

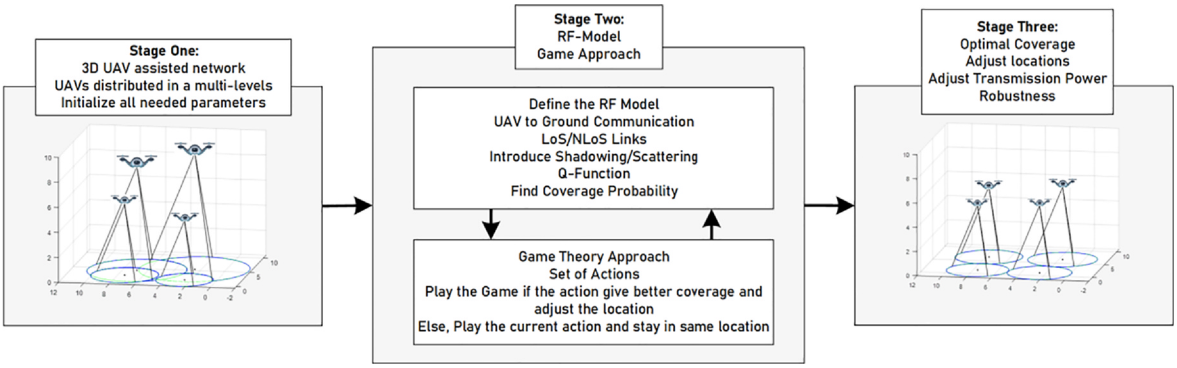

Fig. 2. Main tasks of the system model.

3. Problem setup and RF model

3.1. Problem formulation

UAVs are characterized to move vertically within a certain altitude values. Examples of the available UAVs: quadcopters, helicopters, and balloons, where most of them are considered under the Low Altitude Platforms (LAP) and it is easy to deploy these devices. In our paper, we choose a square region RxR to be the candidate region. M UAVs is distributed in this region in a multi-level with different initial locations (x_k, y_k, z_k) to cover as they can ground users (i.e. vehicles). In this model, we select the quadcopter as our UAV in order to be more realistic scenario, since we use its specification in our simulation part. In the following subsection, we are going to introduce the Radio Frequency (RF) model and show how it is related to the coverage problem. Fig. 2 shows the main stages of this game approach.

3.2. RF propagation model

UAV to ground communication is divided into two propagation links, the first one is related to the Line of Sight (LoS) or Near-Line of Sight (NLoS) conditions, and the second one is with no LoS but still the UAV can cover ground users by the reflections and the diffractions from the main signal. As described in Fig. 3, the radio signals that transmitted by the UAV move in the space with no obstacles, which represents the free space until hitting the urban area. Within this area, the signals suffer from the shadowing and scattering problems that caused by the surrounding building and other things distributed in that area. Hence, this affects the UAV to ground link and cause some losses on the transmitted signals. The Doppler shift effect that results from the mobility of UAVs is assumed to be perfectly adjusted.

The UAVs have similar characteristics with same transmission power and distributed at specific position in the candidate region. UAVs consist from a directional antenna for sensing purposes with a specific beam angle (ϑ_d) in degrees and the gain can be evaluated based on paper (Venugopal et al., 2016) as follows:

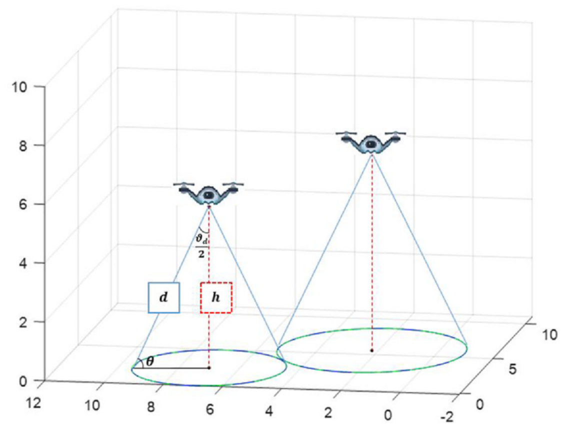

Fig. 3. Diagram of 2-UAVs at different levels to cover a specific region.

$$Gain = \begin{cases} \frac{29000}{\vartheta_d^2}, & -\frac{\vartheta_d}{2} \le \varphi \le \frac{\vartheta_d}{2} \\ \frac{1}{\sin^2\left(\frac{3\pi}{2\times\sqrt{N_0}}\right)}, & otherwise \end{cases} \tag{1}$$

where φ represents the sector angle, $\frac{29000}{\vartheta^2}$ represents the gain of the main lobe for the directional antenna, $\frac{1}{\sin^2(\frac{3\pi}{2\times\sqrt{N_0}})}$ represents the side lobe gain and N_0 is the number of antennas in the UAV.

Each UAV to ground link has a coverage probability and it depends on the environment and the locations of UAVs and ground users. The shadowing and scattering effect in NLoS is higher than LoS. Based on (Al-Hourani et al., 2014) and the previous explanation, the received signal power can be defined from UAV_k to any ground user as follows:

$$P_{user,k}(dB) = \begin{cases} P_t + Gain - L_{dB} - \chi_{LoS}, & LoS \;\; Link \\ P_t + Gain - L_{dB} - \chi_{NLoS}, & NLoS \;\; Link \end{cases} \tag{2}$$

where $P_{user,k}$ is the received signal power, $Gain$ represents the antenna gain in dB, P_t represents the transmission power of the UAV, and L_{dB} represents the path loss value and can be defined as follows:

$$L_{dB} = 10 \times n_0 \times \log\left(\frac{4\pi f_c d_k}{c}\right) \tag{3}$$

where f_c represents the carrier frequency of the transmitted signal, d_k is the distance between the UAV and the ground user, c is the speed of light, and n_0 represents the path loss exponent and can be chosen based on (Ahmed et al., 2016). χ_{LoS} and χ_{NLoS} represent the shadowing effect with normal distributions $N(\mu_{LoS}, \sigma^2_{LoS})$ and $N(\mu_{NLoS}, \sigma^2_{NLoS})$, respectively for LoS and NLoS links. μ is the mean and σ^2 is the variance of this distribution. However, the variance of this distribution based on (Al-Hourani et al., 2014) is related to the environment and the elevation angle and can be defined as follows:

$$\sigma_{LoS}(\theta_k) = k_1 e^{(-k_2\theta_k)} \tag{4}$$

$$\sigma_{NLoS}(\theta_k) = g_1 e^{(-g_2\theta_k)} \tag{5}$$

where $\theta_k = \sin^{-1}(\frac{\Delta h = h - 0}{d_k})$ represents the elevation angle between the ground user and UAV_k, (k_1, k_2, g_1, g_2) define as constant values based on the environment. Based on the above definitions, LoS and NLoS probabilities can be evaluated as follow:

$$P_{LoS,k} = \alpha \times \left(\frac{180}{\pi} \times \theta_k\right)^{\gamma} \tag{6}$$

$$P_{NLoS,k} = 1 - P_{LoS,k} \tag{7}$$

where α and γ are constant values related to the environment. Also, the sensing/coverage radius can be evaluated as $\le (\Delta h \times \tan(\frac{\vartheta_d}{2}))$. From the previous equations of the UAV to ground model, the coverage probability can be defined as follows:

$$P_{cov} = P_{LoS,k} \times Q\left(\frac{P_{min} + L_{dB} - P_t - Gain + \mu_{LoS}}{\sigma_{LoS}}\right) + P_{NLoS,k} \times Q\left(\frac{P_{min} + L_{dB} - P_t - Gain + \mu_{NLoS}}{\sigma_{NLoS}}\right) \tag{8}$$

where $P_{min} = 10\log(\beta N + \beta\bar{I})$ represents the minimum received power, β represents the signal to interference and noise ratio, N is the noise power, Q is the Q-function, and $\bar{I}$ represents the mean of the interference received power from the closest UAV_m and can be defined as follows from (Mozaffari et al., 2016):

$$\bar{I} = P_t\left(\frac{1}{\sin^2\left(\frac{3\pi}{2\times\sqrt{N_0}}\right)}\right) \times \left[10^{-\frac{\mu_{LoS}}{10}} \times P_{LoS,m} + 10^{-\frac{\mu_{NLoS}}{10}} \times P_{NLoS,m}\right] \times \left(\frac{4\pi f_c d_k}{c}\right)^{-n_0} \tag{9}$$

From the coverage probability equation, we note that changing the altitude of any UAV_k changes the coverage directly due to the distance change, LoS/NLoS probabilities, and the sensing radius. Clearly, if we move the UAV to a high level, the path loss and LoS probability increases accordingly. Moreover, decreasing the distance between UAVs directly increase the interferences. Hence, it is better to adjust the transmission power to achieve the best coverage with less interferences.

4. A potential game approach for optimal coverage

The previous section presented the criterion for evaluating the coverage probability of any UAV with respect to the UAV to ground link and the characteristic of the UAV. In this section, we formulate our problem using a game theory approach, where the coverage probability function represents the utility/payoff function for each player in our game that will be used in order to achieve the optimal coverage. Then, we present the main assumptions and suitable setting that will be used to solve our coverage problem with minimum interferences and power requirements for known region.

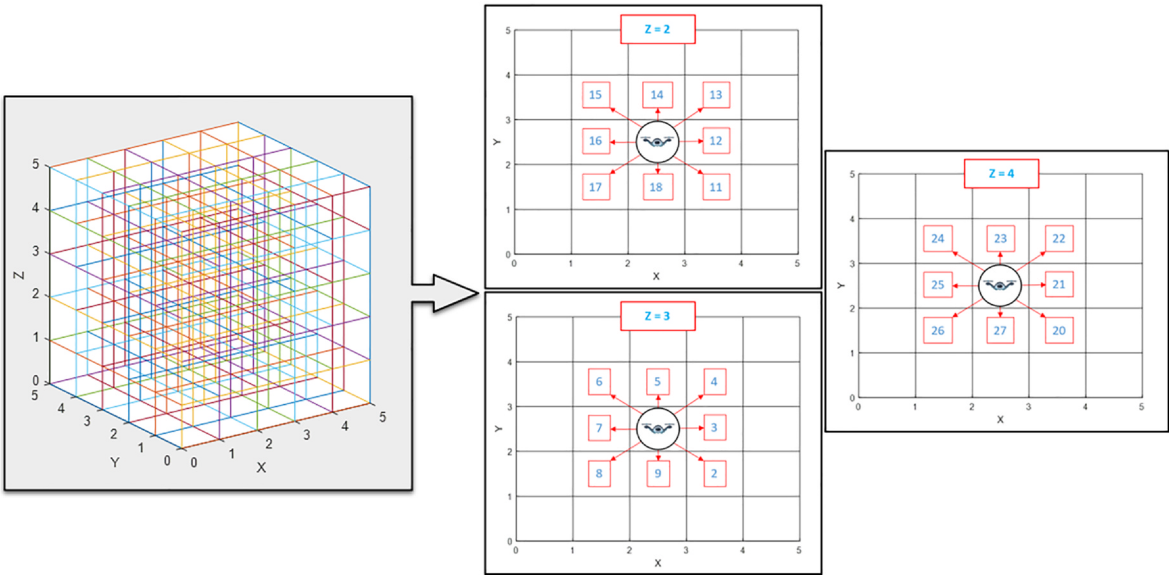

Fig. 4. Next movement of a UAV based on set of actions in 3D space.

4.1. Game description

Game theory is used for analyzing and simplifying the interactions between the players in any network in order to do their tasks either in a cooperative or a competitive manner, which is suitable especially for dense and dynamic networks. Hence, our players will be represented as decision making units in order to decide the suitable action that might achieve better coverage value. So that, UAVs can work and interact using the best strategies in a smart way. In general, any game consists of three elements:

1) A set of players, where our players are the UAVs: UAV = UAV1, UAV2, …, UAVM.
2) A set of strategies/actions for each player (UAV), where this set represents the next movement of the UAV in three dimensional (3D) locations. So, each player has 27 actions in each iteration, either it stays in the same location or moves to the next block (up, down, east, west, south, north, and all diagonal directions): ${S^{3D}}_{UAV_{1,\dots,M}} = \{s_1, s_2, \dots, s_{27}\}$. On the other hand, there are only 9 actions for each player in the two dimensional (2D) space, either it stays on the current cell or moves to a new cell (east, west, south, north, and 4-diagonal directions): ${S^{2D}}_{UAV_{1,\dots,M}} = \{s_1, s_2, \dots, s_9\}$ as illustrated in Fig. 4. Knowing that the current UAVs' movements and the directions are independent to the previous movements and it basically depends on the achieved utility value for each UAV. In our game, the action set for each UAV has 27 options in 3D, either it will stay in same place or it will move to one of the next 26 options based on the best utility value.
3) A set of payoff/utility values for each player based on the selected action $v_{UAV_{1,\dots,M}} = \{v_1, v_2, \dots, v_{27}\}$. In our problem, the utility function represents the covered region by the player with respect to the coverage probability function that was discussed in the previous section.

From the above description, each player chooses a specific action that maximize its coverage (payoff) value. The suitable action will be chosen from the set of our predefined mixed strategies, the selected action is basically selected based a certain probability value, which represents the next cell/block in the candidate region for the current player. At this point, the system might reach an equilibrium point, when there is no extra benefit for making a new movement, since this might reduce the player's payoff, and such situation is called a Nash equilibrium point.

4.2. Game implementation

The main goal of each player (UAV) is to maximize its payoff by exploring new grid locations. To do this, each *UAV* in the UAV assisted network has its own action set sequences that might achieve this goal. Each one has restrictions on its action set and the actions can be used in one iteration to the next in order to reach the Nash equilibrium point that might achieve the optimal coverage value. We analyze our game based on dependent action set for each UAV with respect to the neighboring UAVs.

The coverage value in the game approach can be found using the aggregate coverage for all points in the candidate region. Hence, we can define the coverage value of each *blocki* in 3D location based on the coverage probability function by using the following equation:

$$T_{i,M} = (1 - \prod_{k \in M} (1 - P_{cov(i,k)})) \tag{10}$$

Based on this equation, we can find the aggregated coverage over the whole candidate region, which represents the payoff of each UAV according to this equation:

$$v_k = \left(\sum_{i\in R^2} T_{i,M}\right) \tag{11}$$

The optimal deployment can be achieved by maximizing the coverage of the whole network:

$$COV: v_M^{optimal} = \text{argmax}v \tag{12}$$

As it will be discussed in the remaining of this subsection, all restrictions on the action set are based on the potential game structure, where the updates follow a learning algorithm that is known as spatial adaptive play (SAP) (Arslan et al., 2007). SAP algorithm achieves better performance for the UAVs networks in term of coordination and cooperation while exploring the candidate region (Ruan et al., 2018; Arslan et al., 2007).

At each time value, one UAV $k \in M$ is randomly selected to update its action and the other UAVs must repeat their current actions $s_{-k}(t) = s_{-k}(t-1)$. During the update process, UAV k chooses an action from its action set $S_{UAV,k}$ based on a such probability value called $p_k(t)$, and it can be evaluated using this equation (Arslan et al., 2007):

$$p_k^{s_k}(t) = \frac{e^{(\tau\times v_k(s_k,s_{-k}(t-1)))}}{\sum_{\bar{s}_k\in S_k}(e^{(\tau\times v_k(\bar{s}_k,s_{-k}(t-1)))})} \tag{13}$$

where s_{-k} represnets the set of actions of all UAVs except UAV_k, $\bar{s}_k$ is the remaining action in the set except the current action, and $\tau = \log(1+t)$ based on (Singh and Chen, 2013) and it represents the likelihood value that force the UAV to choose a suboptimal action, if $\tau = 0$ the UAV choose any action $s_k \in S_k$ with equal probability and when $\tau \to \infty$ UAV chooses an action that gives the best payoff with a high probability value as follows:

$$\{s_k \in S_k: v_k(s_k, s_{-k}(t-1)) = \max_{\bar{s}_k\in S_k} v_k(\bar{s}_k, s_{-k}(t-1))\} \tag{14}$$

We represent our coverage payoff function as a potential function over the candidate region:

$$\varnothing(s_k, s_{-k}) = \sum_{i\in R^2} v_{k,i}(s_k, s_{-k}) \tag{15}$$

Given the above potential function, each UAV does not need to know the decision of other UAVs to calculate its payoff for a specific action, while taking in their account the new movement will not make the UAV overlap with the coverage radius of the neighboring UAVs. Suppose that one UAV tries to change its state from $S1$ to $S2$ in one movement, we can evaluate the variation that occurs in the potential function as follows:

$$\begin{aligned}
\Delta\varnothing &= \varnothing(s_{k,S1}, s_{-k}) - \varnothing(s_{k,S2}, s_{-k}) = \textstyle\sum_{i\in R^2}(v_{k,i}(s_{k,S1}, s_{-k}) - v_{k,i}(s_{k,S2}, s_{-k}))\\
\Delta\varnothing &= \varnothing(s_{k,S1}, s_{-k}) - \varnothing(s_{k,S2}, s_{-k}) = \textstyle\sum_{i\in R^2}(v_{k,i}(s_{k,S1}, s_{-k}) - v_{k,i}(s_{k,S2}, s_{-k}))\\
&= \textstyle\sum_{i\in R^2} T_{i,M}(s_{k,S1}, s_{-k}) - \sum_{i\in R^2} T_{i,M}(s_{k,S2}, s_{-k})\\
&= \textstyle\sum_{i\in R^2}(1 - \prod_{k\in M}(1 - P_{cov(i,k)}(s_{k,S1}, s_{-k}))) - \sum_{i\in R^2}(1 - \prod_{k\in M}(1 - P_{cov(i,k)}(s_{k,S2}, s_{-k})))\\
&= \textstyle\sum_{i\in R^2}(\prod_{k\in M}(P_{cov(i,k)}(s_{k,S1}, s_{-k}))) - \sum_{i\in R^2}(\prod_{k\in M}(P_{cov(i,k)}(s_{k,S2}, s_{-k})))
\end{aligned} \tag{16}$$

Based on the above equation, same UAV characteristic, and same neighboring UAVs for UAV_k in one movement, the above equations can be simplified as follows:

$$\varnothing(s_{k,S1}, s_{-k}) - \varnothing(s_{k,S2}, s_{-k}) = v_{k,i}(s_{k,S1}, s_{-k}) - v_{k,i}(s_{k,S2}, s_{-k}) \tag{17}$$

Therefore, the difference in the payoff between $S1$ and $S2$ is equal to the difference in the potential functions and there is at least one Nash equilibrium point for the whole network based on the definition of the potential game.

We summarize the main steps of our proposed approach as described in Algorithm 1:

Algorithm 1: Potential Game Exploration Algorithm

Initialize time value, actions, UAV locations, RF model parameters
for{$t \leftarrow 1$, max time steps} **do**
  Select randomly one player(UAV)
  if{Player should explore based on $p_k(t)$} **then**
    Compute v_k for all actions
    Play based on the maximum value of v_k and update UAV_k's location
  else
    Play the current action and stay in the same location
  End if
  Calculate $p_k(t)$
end for

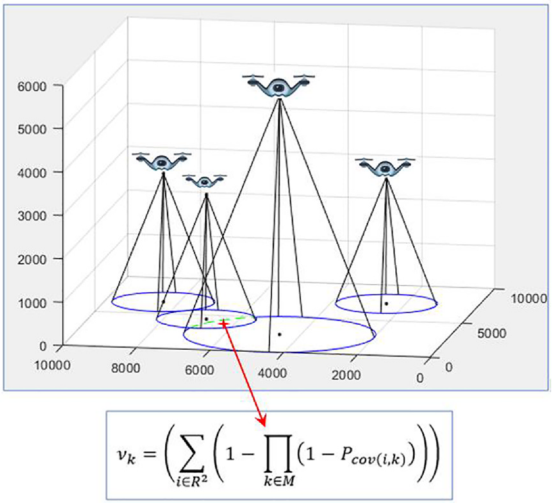

Fig. 5. Total aggregated coverage over the candidate region using 4-UAVs.

5. Simulation results and discussions

This section shows the effectiveness of the proposed potential game based approach according to the achieved optimal coverage value, adaptability with respect to any dynamic environment changes, and network robustness under any failure. We start with a description of the network and then show the results of our game based approach. The simulation scenarios executed on a personal computer that has Intel Core i7-7500U, 8 GB memory and Windows 10 using MATLAB version R2018a. In order to acquire better performance, we repeat the deployment scenarios 100 times and then we calculate the mean of output parameters.

5.1. Mission scenario and parameter settings

1) Payoff/Utility function:

The aggregated coverage value over the whole candidate region represents the payoff function of each UAV and can be evaluated based on this equation:

$$v_k = \left(\sum_{i \in R^2} (1 - \prod_{k \in M} (1 - P_{cov(i,k)})) \right) \tag{18}$$

We consider that our UAVs in the network are distributed in a multi-level style with different initial positions (x_k, y_k, z_k) as illustrated in Fig. 5. Each UAV tries to achieve the best payoff value with respect to its neighbors as well the surrounding environment. Each time step one UAV achieves a certain level of reward for the current action. This reward value changes with respect to the number of the neighboring UAVs. However, this reward value is mainly shared with other UAVs, and each individual UAV's payoff is calculated as the summation of all covered cells in the candidate region either for the current action or for the next movement.

2) Parameters setting:

We have 11 UAVs and they are randomly distributed in a square region $R = 10K$, where these initial positions has no effect on the final results for the deployment problem. Our region is divided into 100×100 cells for finding the covered cells by each UAV at any time, we also have a prior information about the candidate region as a first step.

3) Communication network:

Given the set of UAVs and their strategies for the game, the network is strongly-connected based on the given parameters in the previous subsection. The communication network environment of this region is considered as urban with different specific parameters: $f_c = 2GHz$, $c = 3 \times 10^8$, $\alpha = 0.6$, $\gamma = 0.11$, $n_0 = 2.5$ and mean and needed constants for the standard deviation of LoS and NLoS links are: $\mu_{LoS} = 1dB$, $\mu_{NLoS} = 20dB$, $k_1 = 10.39$, $k_2 = 0.05$, $g_1 = 29.06$, $g_2 = 0.03$. Furthermore, each UAV has 16 antennas and the transmission power range is between $25dBm$ and $45dBm$ for some realistic values, the signal to interference and noise ratio $\beta = 5$, and the noise power $N = -120dBm$. The above specifications and other needed setting based on previous researches (Mozaffari et al., 2016; Ruan et al., 2018; Salah, 2013; El Kafhali and Salah, 2017).

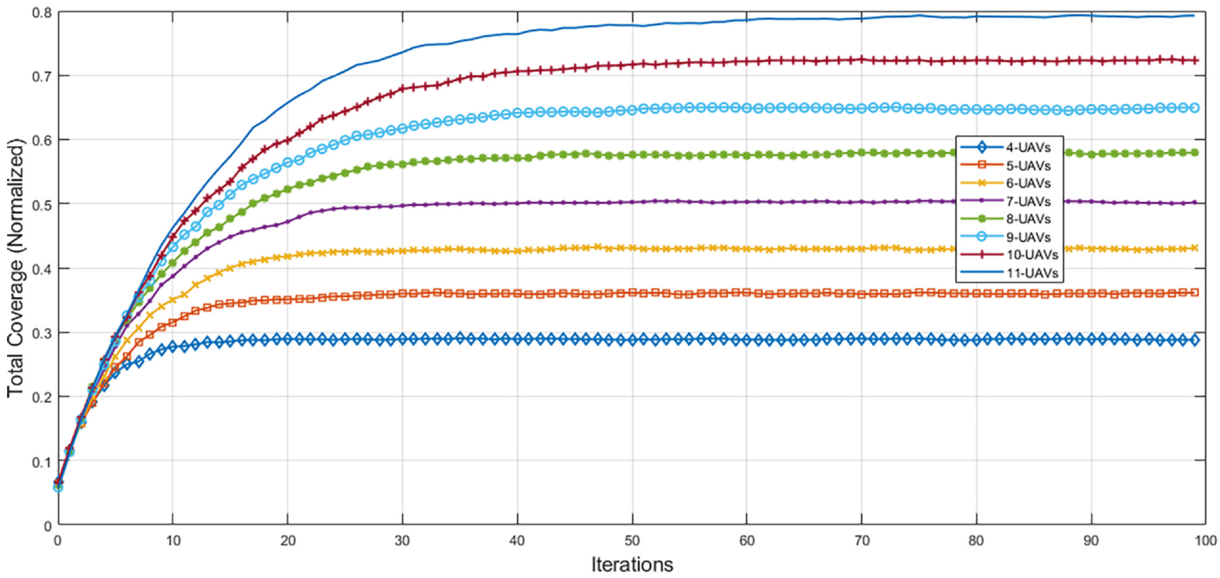

Fig. 6. The covered region for different set of UAVs using game approach.

5.2. Optimal coverage

We demonstrate our experiment for coverage problem over the candidate region without any obstacles between the UAVs and no failures. We also investigate the effectiveness of the cooperation between the UAVs using our proposed approach.

Fig. 6 shows the overall covered area (normalized) with respect to the number of iterations or time unit for different number of UAVs ($M = [4, 5, 6, 7, 8, 9, 10, 11]$) that are distributed in a multi-level network with transmission power equals to $35 dBm$. This figure represents the main output of our game where each UAV either plays new action and then change its location or play the current action and stay at same location; this mainly depends on the resulted payoff value of each UAV. We notice that increasing the number of UAVs increase the covered region using the same transmission power and initial locations. However, increasing the number of UAVs in the same network might increase the overlapping region and interferences with the neighboring UAVs. In our simulation scenario, we try to minimize the interference problem as much as possible by keeping UAVs far from each other with a distance equal to or greater than the sum of their sensing radiuses. The output curves of Fig. 6 can be divided into two parts; in the first part, the coverage is dramatically increased, each UAV is playing the game to achieve the highest coverage value with respect to other UAVs. The second part represents the steady state region and it shows that all UAVs reached their maximum coverage value. The error value between any two consequent points is very small and no benefit is achieved if we continue playing same game. Furthermore, the number of needed iterations to reach the steady state region using 4-UAVs is less comparing with 5-UAVs and other scenarios. However, the covered region in the 11-UAVs scenario is the highest comparing with other scenarios with high number of iterations also. Some of the plotted curves did not achieve the targeted value of coverage (< 0.5) as well the communication model did not achieve the demand of communication.

Fig. 7 represents the relation between the covered region (normalized) and the transmission power for the 11 UAVs network. We notice that increasing the transmission power directly increases the covered region because that the coverage value is related to the characteristics of the used RF model. The curve starts with a small value and keep increasing with the number of iterations until reach the maximum coverage value that can be achieved by using any power value $[25, 30, 35, 40, 45] dBm$. Moreover, it is clear from the Fig. 7 that increasing the power value increases the covered region and the interferences between the neighboring UAVs, which affects the whole network. However, the output curves converge to a constant value, which represents the maximum coverage that can be achieved using this transmission power.

5.3. Adaptability and robustness

We study the robustness and investigate the situations when unexpected failures occurred in our UAVs assisted network. Once this occurs, all non-failure UAVs adjust their location directly in order to achieve the best response using their maximum transmission power.

Fig. 8 shows the covered area with respect to the number of iterations for 10-UAVs assisted network when one of the UAVs got lost and stop working. In this scenario, one UAV is lost after around 80 iterations and then the network tries to reach the best coverage value by using the available maximum transmission power. We notice that same behavior is shown for the 8 and 9 UAVs, the curve goes to a dip region for specific number of iterations due to discontinuity resulted from the non-operating UAV, and then the curve start adjusting the coverage value for the whole network based on the transmission power in order to reach the best response or even

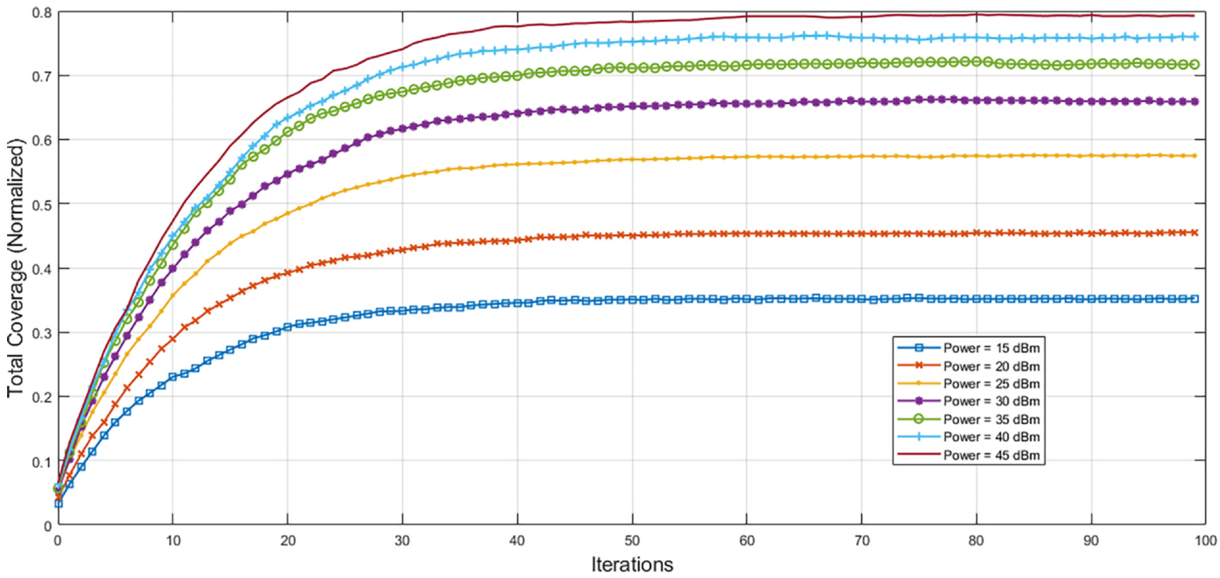

Fig. 7. Overall coverage for different transmission powers in 10-UAVs network using game approach.

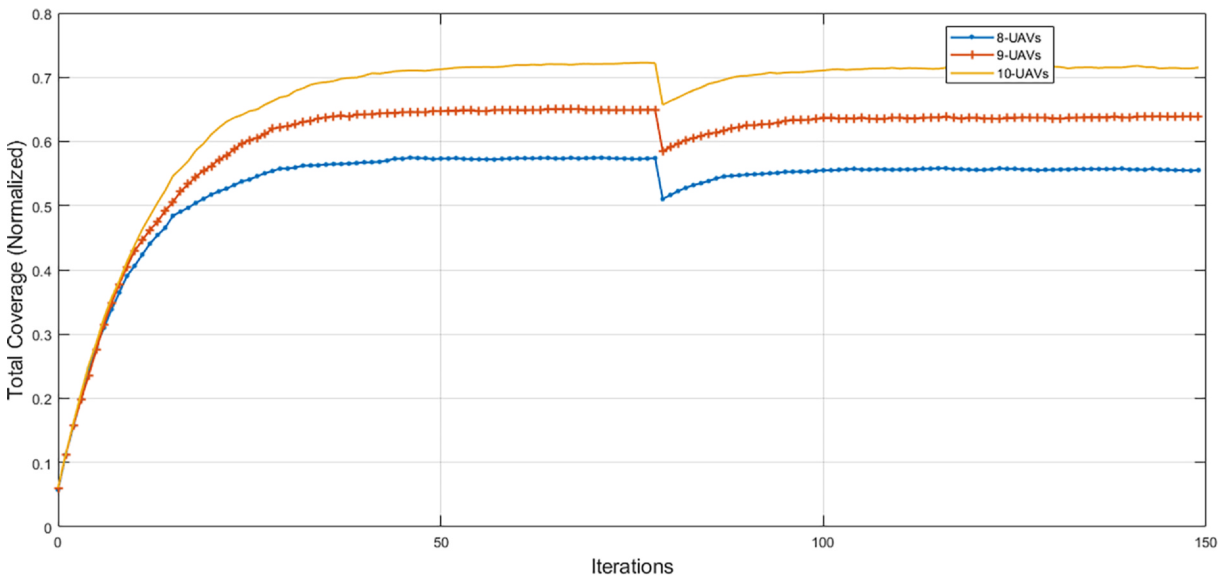

Fig. 8. Impact on a UAVs assisted network when one UAV stop working using game approach.

same NE point. This result is obtained after around 30 iterations from the dip region. We tried new experiment by adding new UAVs in the UAVs network for studying the new behavior of the network, we notice that adding new UAV increases the needed relatively number of iterations because some of the existing UAVs might be sharing some regions with other UAVs, which cause the interference problem. We notice also the iterations may increase in some unpredictable environments, though the proposed approach is still able to reach the Nash equilibrium value.

5.4. Comparison with a non-game theoretic approach

We compare our game theoretic approach against one of the traditional non-game theoretic approach (Papatheodorou et al., 1612). We chose this approach for the following reasons:

1. It is a non-game theoretic approach and we need to study the behavior of the non-game approach with respect to the game-theoretic approach.
2. It is a light and simple approach compared with other non-game approaches that discussed in the related work section.

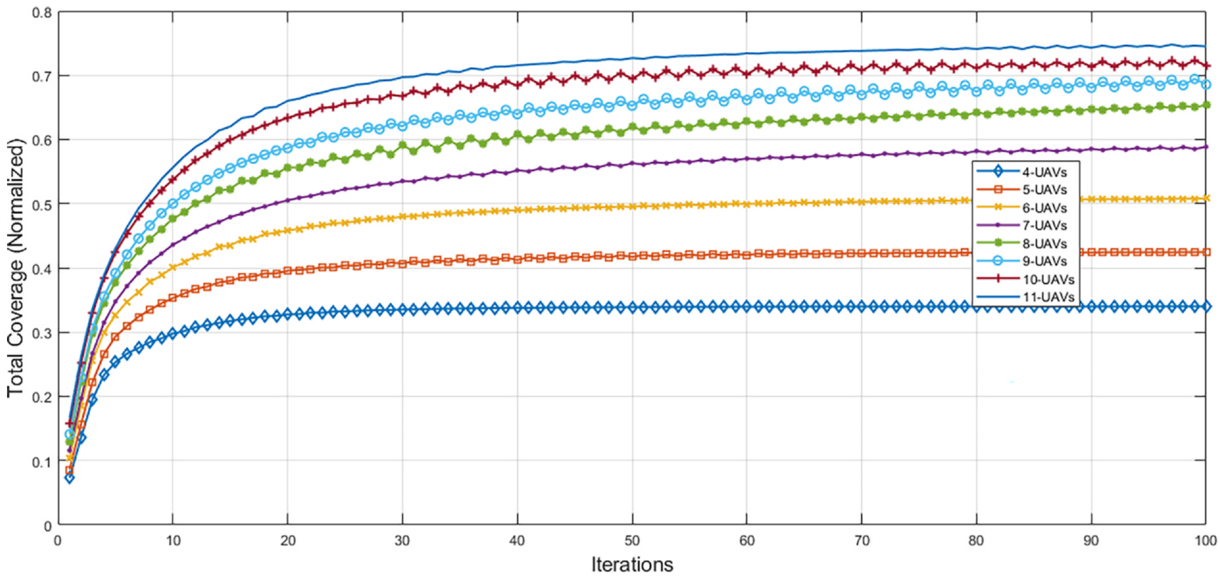

Fig. 9. The total coverage for different set of UAVs using non-game approach.

3. Both approaches depend on their downward facing camera (directional antenna) for achieving the required coverage.
4. The altitude and the sector angle of the UAV are the main variables in both approaches and they can be adjusted to achieve the best coverage.

The setting of the main simulation parameters are as follows:

We randomly distribute UAVs ($M = \{4, 5, 6, 7, 8, 9, 10, 11\}$)in a square region 10 K by 10 K at different locations (X, Y, Z), the range of the altitude Z is based on the low altitude platforms range, the angle ($\frac{\vartheta_d}{2}$) is adjusted to reach 45 degree, and we repeat our simulation 100 runs and use the average value in our figures. The performance metrics are the overall coverage (normalized) with respect to different set of UAVs and how many iterations are needed to reach the optimal coverage for each set of UAVs.

Fig. 9 shows the covered area with respect to the number of iterations or time unit for different number of UAVs ($M = [4, 5, 6, 7, 8, 9, 10, 11]$) distributed randomly in a multi-level network using non-game theoretic approach. Fig. 9 represents the output of selected approach where each UAV tries to adjust its location based on a coverage-quality criterion in order to achieve a good coverage value for the whole network and reduce the interference with the neighboring UAVs. This approach is based on a control law that increases the coverage and reduces the interference at the same time by adjusting the altitude of the UAVs under same initial conditions and candidate region. Moreover, the UAVs try to cover only the candidate region based on their new altitudes and sensing radiuses. The curve can be divided into two regions; the first region where the coverage is dramatically increased when the UAVs try to do the coverage task as well minimize the interference with other UAVs. The second region represents the steady state region and it shows that all UAVs converge to the maximum coverage and the difference between any two consequent iterations is very small and it is negligible. Furthermore, the needed iterations to reach the steady state value using 4-UAVs is less than that with the 5-UAVs and other scenarios. The covered value for 11-UAVs scenario is the highest value compared with other scenarios, nonetheless, it needs more number of iterations. The normalized total coverage is between 0.2 and 0.7 for the selected number of UAVs, however, some of curves did not reach an acceptable coverage value (< 0.5)as when $M = (4, 5)$, where the communication model is not achieving the communication demand. On the other hand, when $M = (6, 7, 8, 9, 10, 11)$ the coverage value is (> 0.5) and this consider as an acceptable value in some practical cases.

Fig. 10 shows the relation between the total coverage and the needed iterations to reach the optimal coverage with respect to the number of UAVs in the network. We simulated the network using a selected number of UAVs $M = (7, 8, 9, 10, 11, 12, 13)$ that achieved more than 50% coverage for the whole candidate region and the used transmission power is $35dBm$. Fig. 10 shows that the game approach outperforms the non-game approach in terms of total coverage for $M = (10, 11, 12, 13)$ and with less number of iterations for all M values. Moreover, Fig. 10 summarizes the results of the two approaches, when the number of UAVs are increased in same square region, the total coverage of the two approaches increases accordingly, however, the increment in the game approach is higher than the non-game approach. Furthermore, the needed iterations to reach the optimal coverage in game approach is less than that of the non-game approach for all M values.

Based on the simulation results, game approach outperforms non-game approach in the coverage ratio with less value of time under same simulation setting when the number of the UAVs = (10, 11, 12, 13). Moreover, the increment in the coverage ratio while increasing the number of UAVs in the game approach is higher and observable comparing with the non-game approach. Moreover, we notice that iterations/time to reach the optimal coverage in game approach is less comparing with the non-game approach regardless the number of UAVs in the network. The reason behind this is that the non-game approach tries to use the maximum

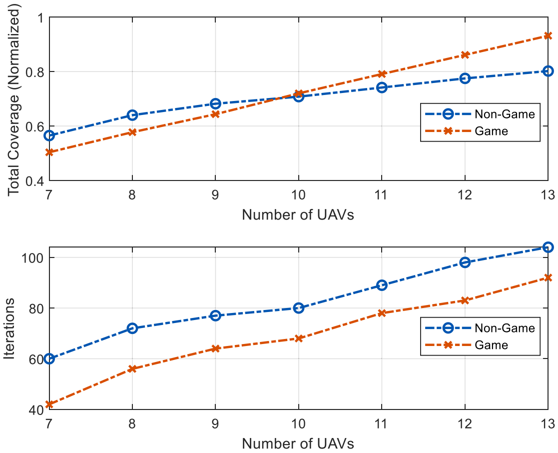

Fig. 10. Total coverage and needed iterations for both game and non-game approaches.

sensing radius for each UAV while avoiding the overlapping problem with the neighboring UAVs. Therefore, in small network this can be done quickly but with increasing number of UAVs, the overlapping region will increase accordingly and this will increase the needed iterations without any overlap to reach the best coverage value. In our game approach, we restricted the next movement of any UAV by considering the overlapping problem from the beginning.

6. Concluding remarks, recommendation and further work

In this paper, we developed a game-theoretical autonomous decision-making approach for an efficient deployment using a multiple UAVs that are distributed in a multi-level and multi-dimensional manner. We studied the deployment problem in term the variation of the coverage probability for each UAV based on the next movement using the minimum transmission power. We designed UAVs' movements as a multi-player game according to a set of actions that might increase the coverage value so that UAV's payoff increases and then it changes its location or it might stay at same location, when the achieved payoff is less than the current value. We considered all specifications of the RF model for LoS/NLoS links in the downlink coverage probability of the UAV to ground communication. Moreover, we presented a mathematical formulation and simulation experiments of the proposed approach. Our approach provides maximum coverage, fast convergence against environmental changes and robust under any failure scenario. The simulation results proved that the effectiveness of our approach in term of achieving maximum coverage based on the selected RF model and the altitude value with minimum iterations using the minimum transmission power. Moreover, the approach showed that when a failure occurred in any UAV, the network adjusts the coverage value based on the maximum power value so that the optimal coverage value can be revisited again. Also, we compared our game approach against the CVAC traditional approach and the simulation results showed that the game approach outperforms the CVAC approach in terms of the coverage value and the computational time. As a further work, we plan to study the energy consumption metric of the UAV assisted network using this game approach including some obstacles between these UAVs in order to study the best path to achieve the maximum coverage value. Moreover, we will include the congestion effect in the utility function of the game approach.

Acknowledgment

The authors would like acknowledge the support of the Computer Engineering Department at King Fahd University of Petroleum and Mineral for this work.

References

Ahmed, N., Kanhere, S.S., Jha, S., 2016. On the importance of link characterization for aerial wireless sensor networks. IEEE Commun. Mag. 54, 52–57.
Al-Hourani, A., Kandeepan, S., Jamalipour, A., 2014. Modeling air-to-ground path loss for low altitude platforms in urban environments. In: 2014 IEEE Global Communications Conference, pp. 2898–2904.
Alzenad, M., El-Keyi, A., Lagum, F., Yanikomeroglu, H., 2017. 3-D placement of an unmanned aerial vehicle base station (UAV-BS) for energy-efficient maximal coverage. IEEE Wireless Commun. Lett. 6, 434–437.
Anicho, O., Charlesworth, P.B., Baicher, G.S., Nagar, A., Buckley, N., 2019. Comparative study for coordinating multiple unmanned HAPS for communications area coverage. In: 2019 International Conference on Unmanned Aircraft Systems (ICUAS), pp. 467–474.
Arani, A.H., Azari, M.M., Melek, W., Safavi-Naeini, S., 2020. Learning in the Sky: An Efficient 3D Placement of UAVs, arXiv preprint arXiv:2003.02650.
Arslan, G., Marden, J.R., Shamma, J.S., 2007. Autonomous vehicle-target assignment: A game-theoretical formulation. J. Dyn. Syst. Meas. Contr. 129, 584–596.
Asl, E.K., Bentahar, J., Mizouni, R., Khosravifar, B., Otrok, H., 2014. To compete or cooperate? This is the question in communities of autonomous services. Expert Syst. Appl. 41, 4878–4890.
Avellar, G., Pereira, G., Pimenta, L., Iscold, P., 2015. Multi-UAV routing for area coverage and remote sensing with minimum time. Sensors 15, 27783–27803.
Balampanis, F., Maza, I., Ollero, A., 2017. Coastal areas division and coverage with multiple UAVs for remote sensing. Sensors 17, 808.
Bekmezci, I., Sahingoz, O.K., Temel, Ş., 2013. Flying ad-hoc networks (FANETs): A survey. Ad Hoc Netw. 11, 1254–1270.

Cabreira, T.M., Di Franco, C., Ferreira, P.R., Buttazzo, G.C., 2018. Energy-aware spiral coverage path planning for uav photogrammetric applications. IEEE Rob. Autom. Lett. 3, 3662–3668.

Charlesworth, P.B., 2013. A non-cooperative game to coordinate the coverage of two communications UAVs. In: MILCOM 2013–2013 IEEE Military Communications Conference, pp. 668–673.

Charlesworth, P.B., 2014. Using non-cooperative games to coordinate communications UAVs. In: 2014 IEEE Globecom Workshops (GC Wkshps), pp. 1463–1468.

Choi, H.-L., Lee, S.-J., 2015. A potential-game approach for information-maximizing cooperative planning of sensor networks. IEEE Trans. Control Syst. Technol. 23, 2326–2335.

Di Franco, C., Buttazzo, G., 2015. "Energy-aware coverage path planning of UAVs. In: 2015 IEEE international conference on autonomous robot systems and competitions, pp. 111–117.

Di Franco, C., Buttazzo, G., 2016. Coverage path planning for UAVs photogrammetry with energy and resolution constraints. J. Intell. Rob. Syst. 83, 445–462.

El Kafhali, S., Salah, K., 2017. Efficient and dynamic scaling of fog nodes for IoT devices. J. Supercomput. 73, 5261–5284.

Fang, T., Tian, H., Zhang, X., Chen, X., Shao, X., Zhang, Y., 2018. Context-aware caching distribution and UAV deployment: A game-theoretic approach. Appl. Sci. 8, 1959.

Garmani, H., Omar, D.A., Baslam, M., El Kamili, M., 2019. UAV-based ubiquitous network access: A Game theoretic analysis. In: 2019 IEEE Global Communications Conference (GLOBECOM), pp. 1–6.

Giagkos, A., Tuci, E., Wilson, M.S., Charlesworth, P.B., 2014. Evolutionary coordination system for fixed-wing communications unmanned aerial vehicles. In: Conference Towards Autonomous Robotic Systems, pp. 48–59.

Giagkos, A., Wilson, M.S., Tuci, E., Charlesworth, P.B., 2016. Comparing approaches for coordination of autonomous communications UAVs. In: 2016 International Conference on Unmanned Aircraft Systems (ICUAS), pp. 1131–1139.

Handouf, S., Sabir, E., 2019. Strategic availability and cost-effective UAV-based flying access networks: S-modular game analysis. Mobile Informat. Syst. 2019.

Jang, I., Shin, H.-S., Tsourdos, A., 2018. Anonymous hedonic game for task allocation in a large-scale multiple agent system. IEEE Trans. Rob. 34, 1534–1548.

Koulali, S., Sabir, E., Taleb, T., Azizi, M., 2016. A green strategic activity scheduling for UAV networks: A sub-modular game perspective. IEEE Commun. Mag. 54, 58–64.

Li, P., Duan, H., 2017. A potential game approach to multiple UAV cooperative search and surveillance. Aerosp. Sci. Technol. 68, 403–415.

Li, Z., Zhou, P., Zhang, Y., Gao, L., 2019. Joint Coverage and Power Control in Highly Dynamic and Massive UAV Networks: An Aggregative Game-theoretic Learning Approach, arXiv preprint arXiv:1907.08363.

Messous, M.-A., Senouci, S.-M., Sedjelmaci, H., 2016. "Network connectivity and area coverage for UAV fleet mobility model with energy constraint. In: 2016 IEEE Wireless Communications and Networking Conference, pp. 1–6.

Mkiramweni, M.E., Yang, C., 2018. Energy efficiency optimization for wireless unmanned aerial vehicle communication networks: A bargaining game approach. In: 2018 10th International Conference on Wireless Communications and Signal Processing (WCSP), pp. 1–6.

Mohammed, F., Idries, A., Mohamed, N., Al-Jaroodi, J., Jawhar, I., 2014. UAVs for smart cities: Opportunities and challenges. In: 2014 International Conference on Unmanned Aircraft Systems (ICUAS), pp. 267–273.

Mozaffari, M., Saad, W., Bennis, M., Debbah, M., 2015. Drone small cells in the clouds: Design, deployment and performance analysis. In: 2015 IEEE Global Communications Conference (GLOBECOM), pp. 1–6.

Mozaffari, M., Saad, W., Bennis, M., Debbah, M., 2016. Efficient deployment of multiple unmanned aerial vehicles for optimal wireless coverage. IEEE Commun. Lett. 20, 1647–1650.

Ni, J., Tang, G., Mo, Z., Cao, W., Yang, S.X., 2020. An improved potential game theory based method for multi-uav cooperative search. IEEE Access 8, 47787–47796.

Orfanus, D., de Freitas, E.P., Eliassen, F., 2016. Self-organization as a supporting paradigm for military UAV relay networks. IEEE Commun. Lett. 20, 804–807.

Papatheodorou, S., Tzes, A., Stergiopoulos, Y., 2016. Collaborative visual area coverage using unmanned aerial vehicles, arXiv preprint arXiv:1612.02065.

Roldán, J.J., Del Cerro, J., Barrientos, A., 2018. Should We compete or should we cooperate? Applying game theory to task allocation in drone swarms. In: 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 5366–5371.

Ruan, L., Chen, J., Guo, Q., Jiang, H., Zhang, Y., Liu, D., 2018. A coalition formation game approach for efficient cooperative multi-UAV deployment. Appl. Sci. 8, 2427.

Ruan, L., Wang, J., Chen, J., Xu, Y., Yang, Y., Jiang, H., et al., 2018. Energy-efficient multi-UAV coverage deployment in UAV networks: A game-theoretic framework. China Commun. 15, 194–209.

Saad, W., Han, Z., Basar, T., Debbah, M., Hjorungnes, A., 2009. A selfish approach to coalition formation among unmanned air vehicles in wireless networks. In: 2009 International Conference on Game Theory for Networks, pp. 259–267.

Salah, K., 2013. A queueing model to achieve proper elasticity for cloud cluster jobs. In: 2013 IEEE Sixth International Conference on Cloud Computing, pp. 755–761.

Sawadsitang, S., Niyato, D., Siew, T.P., Wang, P., Nutanong, S., 2020. Shipper Cooperation in Stochastic Drone Delivery: A Dynamic Bayesian Game Approach, arXiv preprint arXiv:2002.03118.

Semasinghe, P., Maghsudi, S., Hossain, E., 2017. Game theoretic mechanisms for resource management in massive wireless IoT systems. IEEE Commun. Mag. 55, 121–127.

Sharma, V., Srinivasan, K., Chao, H.-C., Hua, K.-L., Cheng, W.-H., 2017. Intelligent deployment of UAVs in 5G heterogeneous communication environment for improved coverage. J. Network Comput. Appl. 85, 94–105.

Singh, C.K., Chen, C.S., 2013. Distributed downlink resource allocation in cellular networks through spatial adaptive play. In: Proceedings of the 2013 25th International Teletraffic Congress (ITC), pp. 1–9.

Venugopal, K., Valenti, M.C., Heath, R.W., 2016. Device-to-device millimeter wave communications: Interference, coverage, rate, and finite topologies. IEEE Trans. Wireless Commun. 15, 6175–6188.

Xiong, Z., Sheng, H., Rong, W., Cooper, D.E., 2012. Intelligent transportation systems for smart cities: a progress review. Science China Informat. Sci. 55, 2908–2914.

Xu, X., Duan, L., Li, M., 2019. Strategic learning approach for deploying UAV-provided wireless services. IEEE Trans. Mob. Comput.