A Survey of Game Theory in Unmanned Aerial Vehicles Communications

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***Abstract*—Unmanned aerial vehicles (UAVs) can be deployed as wireless relays or aerial base stations to improve network connectivity and coverage in cellular networks. UAVs can also be used to significantly enhance the performance of mobile ad-hoc networks and wireless sensor networks. In the future, UAVs are expected to become an integral part of the fifth generation wireless networks as well as key enablers of the coming massive Internet of Things. However, there are still many challenging issues in designing architectures and deployment of UAV-based networks. To address the issues, game theory has recently been adopted as an effective tool for modeling and analyzing problems in UAV-aided networks. In this paper, we survey the applications of game theory in solving various UAV-assisted networks challenges. We first provide a brief introduction to wireless communications with UAVs and then introduce basic game theory concepts and their relation to wireless networks. We further present the classification and brief introduction to the games applied to solve problems in UAV-aided networks. We then provide a comprehensive literature review on game-theoretic techniques utilized in dealing with challenges in the UAV-based wireless networks. Finally, we introduce advanced distributed schemes for interference management in large UAV-assisted communication networks. This paper aims to provide readers with an understanding of UAV-aided networks in terms of their architecture, benefits, challenges, and various game theoretical solutions applied to these communications networks.**

***Index Terms*—Game theory, mean field game, reinforcement learning, UAVs, wireless communications.**

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I. INTRODUCTION

UNMANNED aerial vehicles (UAVs) are expected to take a significant part in the future scientific and technological development. Improved endurance, usability, survivability, and functionality, have allowed the highly advanced UAVs to be used for both military and commercial purposes. For instance, it is estimated that, due to the availability, accessibility, low cost, and high mobility, UAVs' operations will surpass manned aircraft operations by 2035 [1]. Currently, UAVs are used for agriculture purposes [2], environmental monitoring [3], search and rescue operations [4], security and surveillance operations [5], disaster management [6], large infrastructure monitoring [7], and terrain mappings [8]. Other applications [9]–[15] include aerial photography, drugs bust, customs and border patrol, data collection, delivery services, first aid provisioning, automatic power meter reading, cloud computing, traffic control, and wireless communications.

The advancements in electronics and sensor technologies expand the application range of UAVs. Equipped with low cost and high performance commercial wireless transceivers such as cellular networks and the IEEE 802.11 [16], UAVs can now be used for providing network coverage and improving connectivity in wireless communications. Because UAVs can easily and swiftly be deployed and maneuvered, UAV-based wireless communications networks are expected to be major networks for providing cost-effective wireless connectivity. For instance, UAVs can be implemented to support or replace damaged network infrastructures [17], [18]. UAVs can be used for collecting, processing, and disseminating data in wireless sensor networks [19] and underwater devices [20]. Moreover, UAVs carrying base stations can be used to provide coverage to ground terminals in particular events such as political gathering or sporting events [21], [22]. UAVs can serve as wireless relays to extend wireless connectivity between distant terminals whose direct links are severely blocked or have weak signal strength [23], [24]. Although UAVs can utilize cognitive radio technology to improve spectrum, security, and their reliability in the networks [25]–[27], they can also be used to optimize spectrum in cognitive radio [28]. In addition, UAVs are suitable for establishment of wireless backhaul, facilitate network content caching, and enhance data offloading and processing for devices with shorter battery lifetime and limited processing capability [29].

It is expected that UAVs will play a key role in advancing future communications networks [30]. For instance, in an ad-hoc manner, UAVs will be used to establish a

TABLE I
THE ADVANTAGES OF USING UAV FOR WIRELESS COMMUNICATIONS

Benefits	Details	References
Cost-effective	UAV-aided wireless communication systems are in general less expensive to build compared to fixed ground base stations.	[19], [35]
Extend coverage	UAVs can act as relays to extend coverage, as well as aerial base stations in areas without cellular infrastructure.	[21]
Improve performance	The maneuverability of UAV to best suit communication environment can improve network performance significantly.	[23], [36]
Enhance connectivity	Maneuverability, movement, and positioning of UAVs can be optimized to improve network connectivity.	[37]
Enhance network capacity	UAVs can be used as intermediate aerial nodes between macro and small cell tiers for improving coverage and boosting capacity.	[38], [39]
Line-of-sight (LoS) communications	Compared to terrestrial networks, UAVs can establish direct LoS communications, which improves the communication performance.	[40]
Swift and easy deployment	UAVs can quickly and efficiently be deployed whenever needed to create an instant communication infrastructure, thus very useful in emergency situations.	[41]
Maneuverability	UAVs are designed with the capability to perform all kind of maneuvers making easy for them to be controlled and maneuvered when managing wireless connectivity.	[42]
Improve data processing	UAVs can provide a means to collect and transfer massive data between IoT devices that cannot communicate over a long range because of their small transmission power	[43], [44]

three-dimensional mobile network to resolve bandwidth challenges in the Internet of Things (IoT) technology [31]. Long-term evolution (LTE) advanced aerial base stations are designed by using UAVs to provide connectivity from the sky [32]. UAV-based small cells are expected to be crucial part of heterogeneous networks assisting in providing ubiquitous connectivity in fifth generation (5G) wireless networks [33]. In mobile networks, flying base stations are considered to be better substitutes for ultra-dense small cells with improved energy efficiency of user equipment [34].

Deployment of UAVs for wireless communications presents numerous benefits compared to terrestrial networks. Some of the advantages of using UAVs for wireless communications purposes are presented in Table I.

The promising potentials of using UAVs for wireless communications has attracted many research efforts. For instance, [45] studies the feasibility of using UAVs mounted with radio transmitters for wireless networks. The feasibility study of radio frequency identification (RFID) on a UAV for locating materials has been done in [46]. Moreover, companies are investing heavily in the use of UAVs for wireless communications, such as high-altitude balloons [47] to provide Internet connectivity in areas with no coverage, and a solar-powered drone to provide Internet connection around the world [48]. Other companies [49], [50], and [51] have started testing the possibilities of using UAVs for the upcoming 5G networks.

Despite of numerous advantages and potential applications, design and deployment of UAV-aided wireless communications networks come with many technical difficulties [40], [52], [53]. Some of the typical challenges categorized according to layers in wireless communication networks are presented in Fig. 1.

- **Physical Layer:** Energy and limited battery life of UAVs are among the significant challenges in UAV-aided networks. The need for power control mechanism is essential to improve performance, computations, communications, and duration of operation of UAVs. To address this critical issue, circular maneuvering of a non-stationary UAV acting as a relay for energy optimizing is proposed in [42]. In [54], authors presented an analytical framework for energy consumption minimization of a fixed-wing UAV by determining its optimal trajectory.
  Another area that needs more attention is the spectrum and data rate allocation optimization. The uncontrolled rate can cause congestion and therefore affect the performance and throughput of the network. Authors in [55] present a joint time allocation, UAV's flying speed and trajectory optimization to maximize spectrum (in bits/second/Hz) as well as energy (in bits/Joule) efficiency. In [56], the algorithm for the management of UAV-aided ad-hoc network dynamic spectrum and rate allocation using link adaptation is proposed.
- **MAC Layer:** Channel allocation in UAV-aided communication networks allows transmitter to choose the channel that offers the best radio conditions and therefore avoid interference from other transmitters. To address the challenge, authors in [57] proposed a MAC layer protocol named Centralized Intelligent Channel Assigned Multiple Access (C-ICAMA) for ground mobile nodes to access UAV. To improve resource utilization efficiency, minimize energy consumption, and enhancing data transmission, new communications protocols need to be designed. For instance, considering the electromagnetic interference and the dramatic changes in channel characteristics, a random access scheme to identify MAC protocols without demodulation is proposed in [58].
- **Network Layer:** Because of high speed, low altitude, and dynamic manoeuver, UAVs demand low latency and low data rate for control and non-payload communications (CNPC) links for their operations, security, and safety navigation functions such as collision avoidance [59]. Other challenges in a network layer include routing protocols, finding a proper root path, and placement for UAVs to improve network capacity, connectivity, coverage, and resource allocations and management for throughput maximization. In addition, network security is a challenging problem because it involves decision making at a different level and timescale. In literature, various non-game theoretic techniques have been proposed to address the above mentioned problems in UAV-assisted

Layer	Challenges	References
Physical Layer	Energy , Power optimization, Spectrum maximization, Rate allocation	[42], [54]-[56]
Data link Layer	Proper channel allocations, Improved communication protocals	[57],[58]
Network Layer	Low latency & low data rate CNPC, Enhanced routing protocols, Proper route path, Resource allocations and management, Network security	[37], [60]-[64]
Transport Layer	Congestion control, Interference management, Transmission control protocols	[65],[66]
Application Layer	Quality of Experience (QoE)	[67]

Fig. 1. Challenges in different layers of UAV-aided wireless networks.

networks [37], [60]–[64]. Proper root path for the UAV to improve network connectivity is presented in [37]. An efficient UAV-assisted network resource allocation algorithm is designed in [60] to maximize the average throughput. In [61], authors presented a computational method for optimal placement of an aerial base station. Routing protocols for fast moving UAV network with low transmission delay are presented in [62]. Authors in [63] proposed a local flocking set of rules for UAVs placement and navigation problem to improve connectivity and load balancing to mobile nodes on the ground. Additional encrypted communication channel and authentication algorithm between ground control station and UAVs are developed in [64] to maintain UAV's control in hijacking problem.

- **Transport Layer:** Congestion control, interference management techniques, and transmission protocols are some of challenges in the transport layer of UAV-assisted networks. In [65], authors study communication links performance between UAVs in the frequency band of 2.4 GHz, taking into consideration high interferences from the radio control unit which use the same frequency band. To minimize congestion, [66] proposed algorithms for an effective UAV dynamic trajectory control.
- **Application Layer:** User quality of experience is another key issue in UAV-aided networks. Quality of experience (QoE) system measures metrics of the annoyance or delightful of end users with services such as Web browsing or TV broadcasts. However, because of the UAVs' dynamic environment, shared and constrained resources, providing QoE requires a coordinated management system. In [67], authors described and designed an architecture for end-to-end quality of service management in distributed real-time embedded systems, which are evaluated using multi-UAV target tracking and surveillance system.

Non-game theoretic methods that are used to address issues in UAV-assisted networks focus on centralized solutions for a particular challenge. Therefore, using such methods require constant communication exchange between UAVs and central authority, resulting in more energy consumption due to immense signal overhead. Moreover, due to mobility and the need for easy management and control, UAV-based networks need to have self-organizing capability. Indeed, the inherent attributes of UAVs such as flexibility, mobility, and adaptive altitude adds to the unique challenges in UAV-assisted networks such as finding optimal 3D placement for maximum coverage and throughput, optimal path and mobility, security and collision avoidance, energy constraints, and interference which demands a suitable mechanism to address them.

However, because of the rational behaviors, environmental dynamics, and the various preferences of nodes in wireless networks, game theory have found extensive applications in modeling, analyzing, and designing distributed schemes for solving various problems in wireless networks [68]. Game theory deals with different problems where multiple players with contradictory objectives strategically interact with each other in a competition. Therefore, it can provide mathematical framework for analyzing and modeling problems in UAV-based wireless communication systems [69], [70]. Contrary to traditional methods, using game theory, efficient and robust distributed algorithms can be designed to address technical issues in UAV-assisted networks [70]. Game-theory based distributed solutions can minimize communication signal overhead, therefore less energy consumption. Game theory allow UAVs to act autonomously and provide network with self-organizing capability, resulting in easy management and control of the network, which is more important for large-scale UAV-based network. Using game theory, players can be allowed to either cooperate or compete while seeking to maximize their outcomes from the game. Therefore, due to operation nature of UAV-based networks, game theory is regarded as an attractive and suitable tool to accomplish the design goals.

In this work, we survey the applications of game theory in UAV-assisted networks. Although there are several surveys related to game theory in wireless communications, there still lack a survey that uniquely focuses on game theory and its applications in solving various issues related to the emerging UAV-based networks. For example, there are surveys of game theory applications in vehicular networks [71], wireless sensor networks (WSNs) [72], [73] and smart grid networks [74]. A survey of repeated games in wireless networks is presented in [75]. There are also surveys on applications of game theory in solving different challenges including, data transmission in wireless networks [76], networking in a layered perspective [77], [78], routing modeling [79], and network security [80], [81]. Recent survey discusses the use of game theory for optimizing radio resource allocation for 4G-LTE network [82]. Different from ours, which survey game theory and their applications in various problems, works in [76], [79], [80], and [82] address only a particular problem in the network. References [77] and [78] surveys game theory in the general network but in a layered perspective approach.

Similar to this paper, [71]–[74] present several game-theoretic models and their applications in a particular network. However, the discussed networks have different characteristics and nature compared to the UAV-aided networks. Some of the characteristics that distinguish UAV-based networks to other networks such as mobile ad-hoc networks (MANETs), WSNs, and vehicular ad-hock networks (VANETs) include radio propagation model for aerial networks; power consumption and network lifetime; computational limitations due to size and weight constraints; adaptability with respect to UAVs' high mobility, node failure, effects caused by changing environmental conditions, and flight path updates; scalability with minimal performance degradation; and application dependent bandwidth and latency requirements [83]. These UAV-assisted networks characteristics amplify the importance of exploiting game theory as a powerful tool to attain desired optimal goals. In addition, because of their mobility and position flexibility, UAVs as players in UAV-assisted networks are faced with more critical decisions to make compared to players (e.g., sensors, terrestrial base station, mobile devices, and fixed devices) of other networks. Among the critical decisions to be made by UAVs are determining their optimal 3D positioning, velocity, trajectory to avoid collisions, interference, invaders, and minimize energy while achieving optimal goals. Game theory can be an important and effective technique to facilitate the intelligent decision making process of UAVs in the network. Thus, studying and using different game techniques to address difficulties in UAV-aided networks is critical.

To the best of our knowledge, there is no survey explicitly discusses the applications of game theoretic models to address issues in UAV-assisted wireless networks. This motivates us to deliver the survey with the comprehensive literature review on game theory and its applications in UAV-aided networks. The primary objective of this survey is to provide an up-to-date, state-of-the-art literatures reviews of what has been done on solving problems in UAV-based communication networks using game theory and identify issues that still remain to be addressed. In particular, the major contributions of this work are summarized as follows:

- We provide a comprehensive overview on the current and future applications of UAVs for wireless communications, their benefits and existing challenges.
- We present UAV-assisted wireless networks and discuss how they can be applied to augment the terrestrial networks or create independent networks.
- We discuss the basics of game theory applied to solve various challenges in UAV-aided networks and their classifications.
- We gather the state-of-the-art research contributions, from the literature on game theoretic approaches used to solve various challenges in UAV-based wireless communication systems.
- We identify open research issues that need further investigation, and proposed distributed frameworks for interference management in the future massive UAV-based networks.

The rest of this paper is organized as follows. In Section II, we describe UAV-aided networks and discuss UAVs' applications in the existing networks and their potential in achieving the future IoT and 5G visions. An overview of game theory is given in Section III, where we provide a brief introduction and definitions of relevant terms used in game theory. We list the basic elements of game theory used in UAV-assisted networks, present the existing game theoretical approaches classification, and provide explanations of each of the games applied. In Section IV we discuss various UAV-aided network architecture and deployment problems and the game-theoretic approaches applied to solve the challenges. The future direction is given in Section V, followed by the conclusion in Section VI.

II. UAV-Assisted Wireless Networks

Depending on the size, design, and payload, aerial platforms have different capabilities for carrying wireless communication transceivers [32]. For example, compared to drones which can lift very limited weights, balloons can carry LTE equipment which weighs more than 10kg. In the light of their capabilities, UAVs can be used as relays to facilitate communications between two devices or networks, and also as low or high altitude aerial base stations to provide network coverage. In addition, UAVs can be used as data collector and disseminator in sensor networks, and for supporting smart transportation networks such as VANET. Aerial platforms are also expected to be IoT key enabler and an integral part of the 5G mobile network. UAV-based systems can enhance caching, provide wireless network backhaul for terrestrial networks, and optimize data offloading and processing for devices with limited computing power. For the aforementioned current and future applications of UAVs, it is clear that because of their features such as mobility, agility, adaptive altitude, and flexibility, the use of UAVs in forming UAV-assisted networks is an escapable. Using UAVs can significantly enhance the performance of existing ground networks in terms of capacity, throughput, coverage, and overall user's QoE. In this section, we present wireless networks in which UAVs are applied in augmenting the existing networks and their potential applications and in future generation networks. We introduce the applications, network scenarios, and main challenges of each UAV-assisted networks.

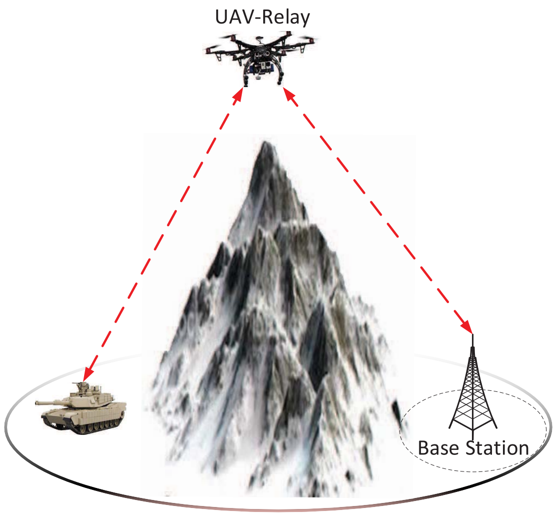

Fig. 2. UAV acting as a relay.

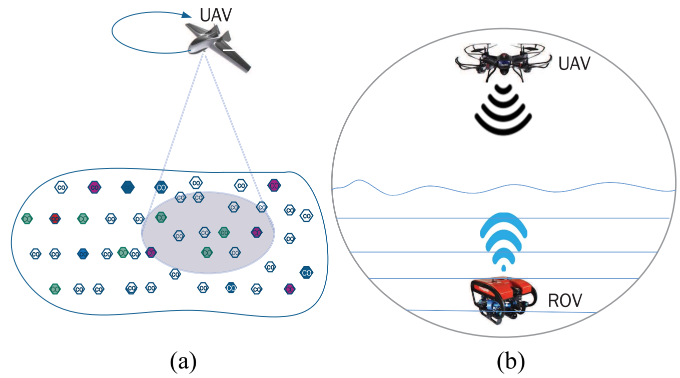

Fig. 3. Applications of UAVs in wireless sensor networks. (a) UAV-based ground sensor network. (b) Drone and underwater body communications.

A. UAV-Assisted Wireless Relays

UAVs are used as wireless mobile relays in the networks. A typical scenario is shown in Fig. 2. In this scenario, UAV is used to relay information between remote user and base station separated by an obstacle, such as mountain. As mobile relays, UAVs have several added advantages compared to traditional ground relays. UAV-aided relays are cost-effective and can easily and swiftly be deployed whenever needed, which makes them very suitable for emergency and temporary events. Moreover, UAVs' high mobility provide an opportunity for enhancing network performance through location adjustment to best suit the environment.

In literatures, [23], [24], [84]–[86], UAV-aided wireless communication relays are studied. UAVs are proposed as relays between network base station and ground base terminals in order to optimize performance in [23]. The throughput of a UAV-enabled mobile relaying system is maximized by optimizing the trajectory of a relay and its power allocations [24]. The cooperative communication between UAV-based relays with a single antenna is investigated to improve the range and reliability of ad-hoc ground networks in [84]. UAVs can be deployed to relay messages between users in areas where there is no communication between receiver and transmitter such as battlefields [85]. Utilizing the advantage of their mobility, UAV relays can be used to minimize network transmission delay [86]. These literature demonstrate the potential of UAVs as mobile relays to improve the performance of wireless networks.

Relaying using UAVs can be an effective technique to improve network throughput, reliability, and extend range of communication. However, UAV-based mobile relays require careful trajectory design which demand techniques that will be able to predict channel variations introduced by their mobility. The challenge is magnified when source and destination nodes are also mobile. In addition to the trajectory, UAVs heading angle to quantify link performance has to be controlled to ensure optimal performance of the ground-to-relay links. To establish and maintain link connectivity, communication protocols for UAV-relays that allow robust, reliable, and adaptation to continuous changes should be developed. Moreover, an efficient cooperation coordination, flight formation, and cluster formation are critical for maximum throughput and energy efficiency when multi-UAV relay systems are deployed.

B. UAV-Assisted Wireless Sensor Network

Wireless sensor networks (WSNs) have wide range of applications. To mention a few, area monitoring, healthcare monitoring, natural disaster prevention, and water quality control. Wireless standards and solutions such as ZigBee, Z-wave, and IEEE 802.15.4 provide wireless connectivity to low power sensors. Among the significant challenges in WSNs are power consumption constraints, low processing capacity, and limited storage capacity of nodes. UAVs carrying wireless devices can be intergraded in WSNs to minimize these challenges. UAVs allow sensors to periodically establish connections rather than having continuous connection with data centers. Thus, UAVs help to enhance network throughput and prolong its lifetime by periodically collect and disseminate data. Fig. 3(a), shows a scenario where a UAV is used to collect and transmit data in larger clustered ground wireless sensor network. In Fig. 3(b), the UAV mounted with wireless device communicates with sensors attached on a remote-operated underwater vehicle (ROV), thus, speeding up the process of data exchange.

Because of the unique potential of UAVs in improving WSNs, many have studied and contributed to the area. In agriculture, a low-cost WSN has been designed in which UAV is used for collecting data and detecting changes in extensively scattered ground nodes which cannot directly connect to each other [19]. In [87], a UAV-aided scheme for collecting data is designed, and four data collection algorithms were developed based on multi-data-rate transmissions and the contact duration time between sensors and UAVs. Data collection, monitoring, and reliability assurance of UAV-based linear WSNs are researched in [88], [89], and [90]. Authors in [91] investigated different opportunities that mobile sensors have in communicating with UAVs in UAV-assisted WSNs. As described in the just mentioned works, the integration of UAVs in WSN architecture will enhance the performance and extend lifespan of the network.

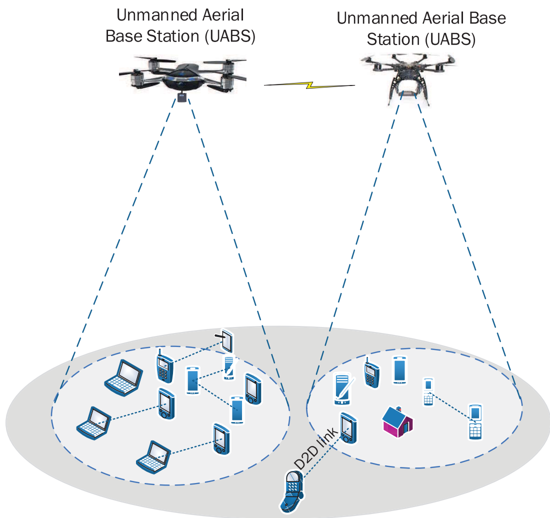

Fig. 4. Unmanned aerial base station (UABS) providing coverage to ground nodes.

To realize UAV-assisted WSNs, there are still challenges to be addressed. For instance, the speed of UAV for optimal network performance, sensor distribution in the network, and conflict when large number of sensors concurrently send its own data to the UAV. To improve network efficiency, designing data gathering algorithm to facilitate the autonomously collection and processing of data becomes necessary. Another challenge in UAV-based WSNs is finding proper deployment of sensors in a large-scale environment to ensure that data from sensors is received and transmitted at a desired rate and reliably. Fast path planning for UAV that will allow collection of data from an initial point to the destination in shortest amount of time and minimum energy need to be designed.

C. Unmanned Aerial Base Stations

After catastrophic natural disasters, or in emergency situations such as political rallies or sports events where there are large gatherings of mobile users, a temporary unmanned aerial base station (UABS) can be used to provide communication coverage [92]. UAVs mounted with communication devices are suitable for providing such an infrastructure due to their two unique characteristics, namely, low cost and fast speed. Fig. 4 depicts a scenario where UAVs equipped with transceivers provide coverage to users on the ground. Aerial base stations can provide service with very high quality due to their ability to establish a line of sight connection. Their placements can also be optimized to provide maximum coverage and throughput.

References [22], [93]–[98] explore wireless communication networks in which UAVs act as aerial base stations. The design, deployment and performance analysis of using UAVs as base stations is studied in [22]. In [93], the flying ad-hoc base station system to provide coverage in the areas where there is overloaded, damaged or no network infrastructure is described. A case scenario where aerial base stations are used for collecting data in the cluster-based device-to-device communication to save energy is given in [94]. Mounted with wireless communication devices, UAVs are investigated for providing a reliable uplink for devices with minimum energy in the Internet of Things [95]. Moreover, UAVs are expected to improve downlink transmission of data [96]. To minimize the needed transmit power of UAV acting as a flying base station, an optimal deployment is investigated in [97]. To extend the line of sight (LoS) range, [98] describes a fast deployable wireless broadband, mobile communication network using UAVs.

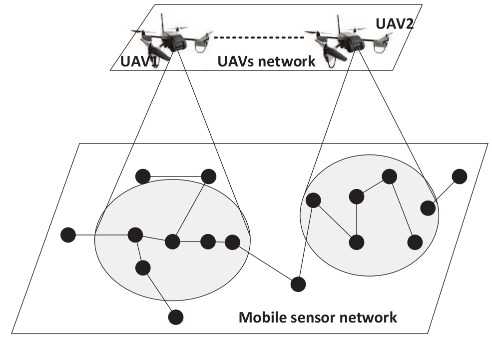

Fig. 5. An example of MANET architecture using UAVs.

Deploying UAV BSs can provide much better performance in terms of coverage, load balancing, spectral efficiency, and user experience compared to existing ground based solutions. The challenges that remains to be solved are finding optimal placement and mobility in 3D space for maximum coverage, power consumption optimization for sustaining the operation of the flying BS, interference avoidance to guarantee quality of experience for users, and network security. Because of their mobility, in depth path loss study is necessary, to determine optimal speed and placement of UAVs, which can provide sufficient signal strength to ground users.

D. UAV-Assisted Mobile Ad-Hoc Networks

The mobility and elevation of UAVs can be leveraged to optimize ground-based mobile ad-hoc networks (MANETs). In MANETs, a small group of nodes is considered as backbone nodes. These nodes are responsible for motion and position coordination, as well as providing connectivity to the disconnected subnetworks. UAVs can be used as MANETs backbone to ensure energy conservation, support multi-hopping, and scalability [99]. Fig. 5 shows an example of MANET architecture using UAVs. UAVs provide connectivity to the nodes on the ground and are responsible for network coordination.

As backbone of MANETs, UAVs become a solution to many challenges, such as linkage, capacity, load balancing, and reliability of the network [100]–[102].

UAVs can improve ground-based wireless MANETs performance by minimizing routing overhead, thus reducing delay and improve throughput. The main challenge of integrating UAV in MANETs is finding mobility strategy that allows continuous connectivity and maintaining flow of information to properly route traffic. UAV mobility strategy and placement should take into considerations high dynamics and autonomous topology of the network, minimize package delays, and allow network scalability. In addition, advanced routing protocols are to be designed for ground backbone

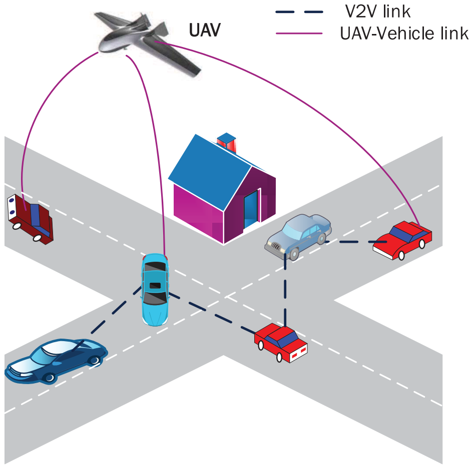

Fig. 6. UAV assisting VANET.

nodes to access UAV to solve the highly asymmetric data traffic in the network. Effective routing algorithms to incorporate MANET backbone and UAVs links to minimize hop-count is of critical importance for minimum delay and power consumption in the network.

E. UAV-Assisted Vehicular Ad-Hoc Network

Vehicular ad-hoc network (VANET) is a subclass of MANET, in which nodes moves in a pre-defined path. Conventional VANET is composed of inter-vehicle communication and vehicle-to-roadside communication. The purpose of VANET is to provide safety management, traffic management, and Internet services to road users. With the increase of mobile vehicles and the expected substantial amount data exchange especially in urban areas, maximization of data throughput and optimization of wireless communications in VANET become indispensable. Moreover, in large cities, it is difficult to find a shortest end-to-end connected path because of vehicles' mobility pattern and various obstructions such as buildings to a clear transmission. UAV comes in hand as a suitable technology for supporting and assisting vehicle to communicate in the midst of such challenges.

A scenario where UAV-equipped with communication devices assists vehicles in communicating is represented in Fig. 6. UAVs can form flying ad-hoc networks to extend the network scalability, survival, and coverage in VANET [103]. In addition, as a unique form of ad-hoc network, UAV-Assisted VANET [104], [105] can be formed to assist vehicle-to-vehicle communications, thus, improving road safety and navigation in urban areas by providing reliable communication.

UAVs will be key components in VANETs and the future intelligent transportation system (ITS) as a whole [106]. However, integrating UAVs in VANET is accompanied with numerous challenges [107]. Among which are, proper data routing protocols for vehicles that are supported by UAVs, path planning, mobility control, and placement of UAVs for optimal data routing for delay tolerant and minimum energy consumption. Apart from providing seamless communication between vehicles, in ITS, UAVs can be road accident report agents, road side units, and flying police eye. Combining all these functions to ensure efficient data gathering, routing, and dissemination is another interesting research area. In urban cities, finding a shortest end-to-end connected path given the vehicles' mobility pattern and the various obstructions such as tall buildings to a clear transmission is a difficult task [104], which becomes more challenging due to high mobility of vehicles.

F. Cache-Enabled UAVs

To improve performance, clients cache and store documents in the browser or network edge. Caching at the intermediate network nodes reduces transmission delay and greatly improve users' throughput [108]. However, due to constant movements of mobile users, caching at static network nodes may not be effective. For static nodes, it requires that the requested contents be cached and stored in multiple nodes so that the mobile user can be served by any of the nodes it requests a content. In this case, additional storage will be needed. Therefore, deploying mobile network nodes can be a useful technique to improve caching efficiency by making easier to track and deliver contents to the mobile users. UAVs are proposed to be the future mobile network nodes that can effectively serve mobile users with popular cached contents by tracking them according to the movement pattern [29], [109]–[111]. In fact, using UAVs for caching can reduce traffic in cellular networks.

It is evident that, deploying cache-enabled UAVs can enhance QoE of users, minimize energy consumption, and reduce congestion in the network [111]. Nevertheless, to realize cache UAV-enabled networks, advanced frameworks for caching and storing most popular contents which are to be delivered to users when requested need to be developed. The frameworks should be able to find user-UAV associations, optimal locations of UAVs, and contents to cache at UAVs due to prediction of users content requests distribution and their mobility pattern. Investigation of an optimal arrangement of UAVs' caching contents and service locations based on context awareness and the influence between environment and users in the network need to be done [112]. Designing of optimal prediction and caching of most popular context strategies according to users habits to improve system efficiency and guarantee transmission performance is of the utmost importance. Other important areas of investigation include security for UAVs to guarantee normal operations and avoid eavesdropped, energy efficiency optimization, and interference management. Moreover, there is a need for joint optimization method that takes into account content caching, transmission, location optimization, and trajectories of UAVs to simplify management of the network.

G. UAVs as Flying Wireless Backhaul

In terrestrial network infrastructure, wired backhaul has been the typical method for transmitting data from core to edge network. Most recently, because wireless equipment are cheaper to purchase and install, and can be rapidly deployed, wireless backhaul has become a viable option [113]. Although wireless backhauling is a promising solution, it suffers from signal loss for longer distance, interference, and blockage that

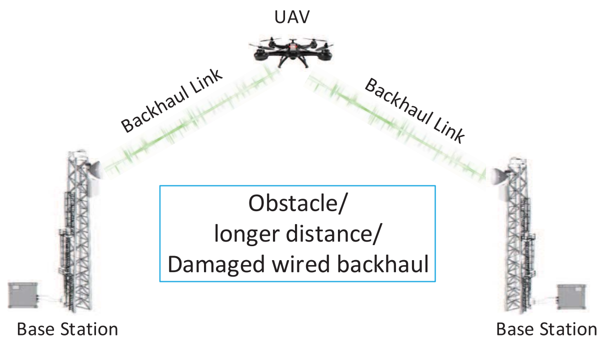

Fig. 7. An example scenario where UAV is used for providing wireless backhaul for two base stations.

degrade radio access network throughput [114]. To solve signal degradation problem due to the distance between radio access, link gain has to be increased by using higher powered larger radios and large dish antennas which is more challenging and costly.

As the viable alternative, UAVs can be used to provide high speed, reliable, and cost-effective wireless backhaul connectivity for networks [115]. Specifically, UAVs can quickly be deployed to replace damaged wired backhaul for terrestrial networks. When optimally placed to establish LoS, UAVs can provide reliable, high data rate communication links. UAVs can be used to provide reconfigurable and flexible multi-hop LoS wireless backhauling for both aerial and terrestrial networks. Fig. 7 shows an example of UAV-based wireless backhauling for two base stations which are either deployed at far distances, or have damaged wired backhaul, or obstructed LoS.

The major bottleneck for realization of wireless flying backhaul include proper positioning of UAVs for efficient data transmission and system performance optimization, interference mitigation, and power management. Backhaul-aware UAV placement schemes are necessary to guarantee minimum movement of the UAV to save power, increase flight time, and minimize channel variations. For better performance, advanced interference mitigation schemes are needed. Moreover, UAVs' security have to be elevated to prevent eavesdrops and guarantee reliable and seemliness connection between UAVs and BSs.

H. UAV-Assisted 5G Networks

The increase of mobile video streaming and massive data exchange has caused an exponential increase in data traffic. It was recently estimated that mobile data traffic grows at the rate of 45 percent, and with the IoT becoming a reality, in the near future, billions of devices will be connected, many of them will be IoT devices [116].

The coming 5th generation (5G) network is visioned to support and provide services to massive devices and meet data traffic demands efficiently. The 5G network needs to have more capacity, higher data rates, lower latency, connectivity for a massive number of devices, reduced energy and cost, and better QoE characteristics [117]. Fig. 8, represents three user cases that 5G network has to support [118]. Firstly, the ultra-reliable low latency communications (URLLC), which is a requirement for emerging critical applications such as industrial Internet, intelligent transportation systems (ITSs), and healthcare, entertainment, financial, and utility provisioning. Secondly, 5G has to be able to provide enhanced mobile broadband (eMBB), which refers to the extended support of conventional mobile broadband through improved average data rates, capacity, and coverage. Thirdly, 5G network has to support massive machine type communications (mMTC), which is necessary to support the envisioned IoT scenario with billions of connected devices and sensors.

To realize the vision, UAVs are considered for the future 5G network architecture [32], [119]. 5G networks are composed of heterogeneous networks. In 5G networks, the UAV-assisted heterogeneous cellular solution is proposed in [120] to provide service to a large number of machine type communication (MTC) devices. To extend coverage and increase capacity in 5G heterogeneous networks, authors in [121] propose an efficient placement of UAV in demand areas. Next generation networks are expected to have minimum delay, to realize that, UAVs are proposed for delay optimization in heterogeneous networks [122].

Cell splitting and densification to form ultra-dense networks (UDNs) is one of the effective means to increase network capacity and therefore improve user experience. UDN is a solution to provide high capacity in 5G networks. UAVs are also expected to be deployed as part of UDNs. For example, in [123] drones are designed for inter-service operability in UDN to increase network reliability.

It is evident that 5G network will be characterized by device-to-device (D2D) communication. D2D communication is the method where devices transmit and receive data between each other on the user plane without having to use network resources. D2D communications can contribute significantly toward meeting goals of 5G. UAVs are included in D2D communications to facilitate better network output. In [60], UAVs are proposed to be energy sources that provide radio frequency for low powered D2D pair to maximize throughput and minimize energy constraints. Minimizing bandwidth usage saves energy, frees frequencies for more capacity, increases data rate, and decreases latency. These gains work together to meet user quality of experience in the 5G network.

Another alternative for meeting band requirement in 5G is the use of millimeter wave (mmWave) spectrum. mmWave is considered by researchers as the way to bring 5G into the future. It is the band of spectrum ranging from 30 GHz to 300 GHz which can be used for ultra-fast 5G mobile broadband [124], [125]. The use of millimeter-wave band technology can be realized by the use of drones. The potential and challenges of mmWave UAV cellular networks are presented in [126].

Integrating UAVs in 5G network is still challenging. 5G network is expected to be multi-tier heterogeneous and dense, therefore proper placement of UAVs in the network is of critical importance. UAVs are to be located and projected for system optimal performance with minimum energy consumption. Security in UAV-assisted 5G network is of utmost importance to provide assurance to user's data security, avoid

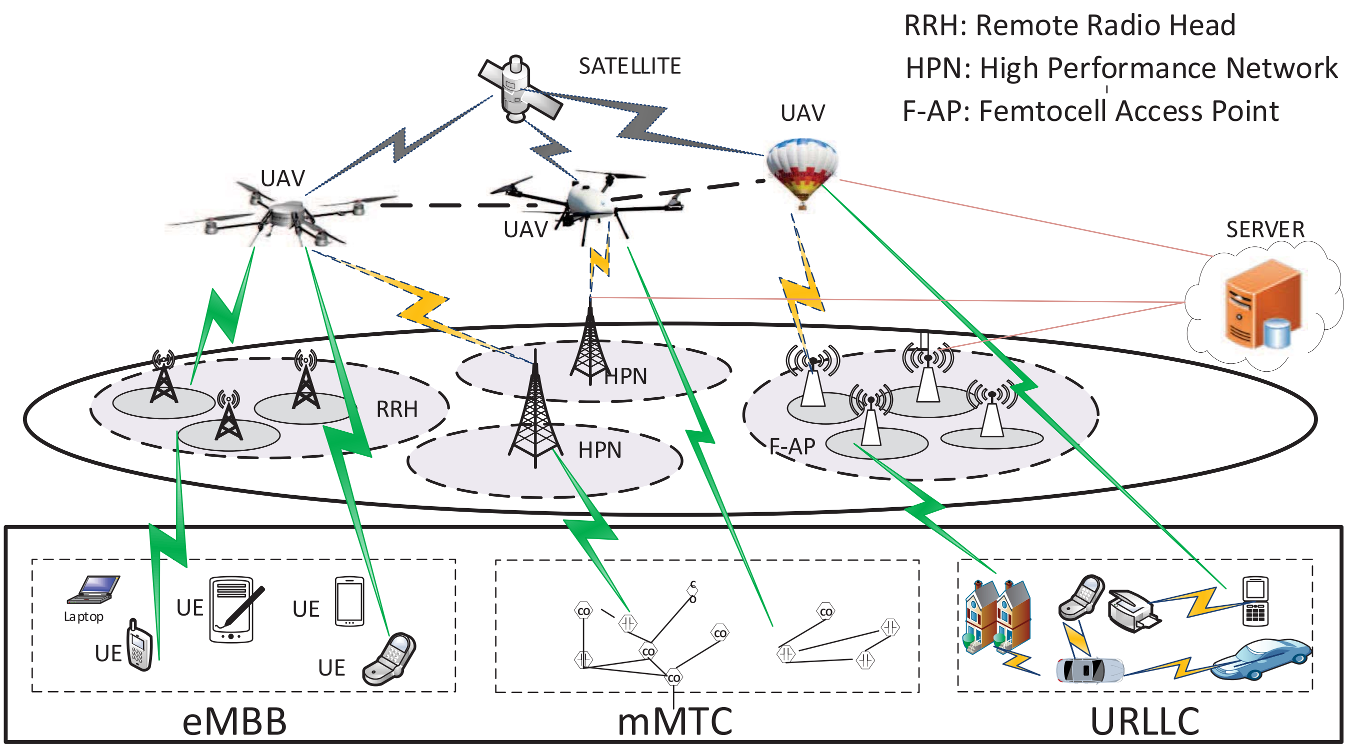

Fig. 8. Scenario examples of the UAV applications in 5G wireless communications network.

eavesdrops, collision with other UAVs or high objects, and guarantee network availability. Various reliable schemes for data routing and protocols are needed in order to boost network efficiency.

I. UAV-Based IoT Communications

Internet of Things (IoT) is expected to form a significant portion of the 5G network [127]. In IoT, massive physical devices that use actuators, sensors, cloud computing, and embedded computing will be connected forming a network of heterogenous applications [128]. The connection among IoT devices requires a reliable wireless communication to guarantee reliable delivery of data at higher rates and ultra lows latency. Moreover, most IoT devices have limited battery power and are not capable of communicating over a long distance, and some of them will be deployed in areas with poor or no wireless infrastructures. The use of UAVs to provide and improve network connectivity is a promising solution to various challenges in IoT. In fact, due to their ubiquitous usability, UAVs are predicted to be key enablers of IoT vision [129], [130]. To address energy limitation problem of devices in IoT, UAVs are proposed in forming energy-efficient mobile architecture in [95]. Contrary to terrestrial base stations, UAVs can significantly enhance communication of massive IoT networks by providing LoS connectivity and dynamically updating their positions according to the pattern activated by IoT devices.

The usage of UAVs signifies their vital role in realizing future IoT, and hence forming of smart cities, hospitals, transportation systems, energy management, and infrastructure management systems. However, since most IoT devices are energy limited, a joint optimization framework for UAVs to simultaneously provide energy and communication-related services to devices is critical. Moreover, more security measures are required, to prevent any possible harm to UAVs and the system in general.

III. Game Theory Meets UAV-Aided Wireless Networks

Game theory is a branch of applied mathematics that is used for describing and analyzing the strategic interaction among multiple decision-makers [131]. The strategic interaction activities are referred to as games where each decision-maker chooses the action that will give maximum possible outcome for self at the same time predicting the rational decision taken by others. Game theory has been applied mostly in the field of economics but has also successfully penetrated into many other disciplines including wireless and communication networks [68], [132]–[135]. There are many different types of game theory; however, in this section, we focus on the games that have been utilized to solve problems in UAV-assisted networks.

A. Fundamentals of Game Theory

In game theory, entities or individuals who make decisions and perform the actions are referred to as players. Depending on the type of game, players can be completely aware or unaware of the action taken by other players or can have partial awareness about the action of other players. In most games in wireless communication systems players have partial or no information about other players. A set of players in a game is usually denoted by $N = \{1, 2..i..n\}$.

Actions are moves taken by players in a particular game. In wireless communication actions can be sending beacon by a mobile device or UAV, changing the location of a device, connecting or disconnecting a device to an available network, switching to another service provider or network, changing modes, say from active to passive mode and others. The set of action is generally denoted by *Ai*.

Strategies are descriptions of how a player could play a game; they are a complete plan of actions throughout the game. Strategies are categorized into two, namely mixed and pure strategies. In a mixed strategy, the probability distribution for all possible actions of a player in a situation are specified, while in a pure strategy, a player takes unique action in a given situation. A set of strategies for every player is donated by *Si*. For example, for any player *i*, the set of strategies is represented as $Si = \{s_1, s_2, s_3 \ldots s_m\}$.

Payoff, also known as a reward is what players receive at the end of game contingent upon actions of all other players in the game. The payoff is determined by action of individual together with the action of competitors. The reward can be negative or positive. A set of payoffs corresponding to the strategies selected by each player is mostly given by $M = \{1, 2, \ldots\}$.

Another key terminology in game theory is Nash equilibrium (NE). NE is basically the solution of a game, defined as the combination of best strategies for each rational player that maximize his own utility, provided the strategies chosen by other players [131]. At the NE, no player has an incentive to deviate from the selected strategy because such action would reduce the payoff of that player. The Nash equilibrium obtained when the best responses of both players coincide is known as pure Nash equilibrium (PSNE). Moreover, NE is known as a mixed strategy Nash equilibrium (MSNE) if there is a probability distribution over the possible range of players' strategies. In [136], simple methods for computing a sample NE in a normal form game of two players and *N*-number of players are presented.

TABLE II
ELEMENTS OF UAV-BASED WIRELESS NETWORK AND THEIR GAME COMPONENT SET REPRESENTATION

Game Component Set	Elements of a UAV wireless network	Comments
Players	UAV/drones and ground nodes	Players are assumed to be rational nodes aiming to maximize their utility function
Strategies	Beaconing periods scheduling, task servicing, relocating UAV coordinates, offloading or not offloading data, choosing the right channel, and evading an intruder	Action related to the functionality being studied.
Payoffs function	Performance metrics such as throughput, delays, encounter rates with ground node, number of nodes covered, and signal to noise ratio,	The players' objective which measures the outcome for the players strategies

B. Game Theory in UAV-Assisted Networks

In the current applications of game theoretical approaches in wireless communications with UAVs, there are three main components of a game. These three components, players, set of strategies, and payoffs are represented by different elements of the wireless network as shown in Table II.

Game theory models can be classified into two main categories, which are non-cooperative and cooperative games. The existing game-theoretic approaches fall under the two branches as shown in Fig. 9. The following subsections gives a brief introduction to game theory presented in the classification.

1) Non-Cooperative Games: Contrary to cooperative games, non-cooperative game theory studies the strategies among interactions between individual competing players [68]. The objective of a player is to maximize its utility by selecting its best strategy exclusively. In other words, in a non-cooperative game, each player is rational but selfish. The game is mainly applied in power control, distributed resource allocation, finding optimal height and position of UAV, congestion control, optimizing UAV coverage, and spectrum sharing in cognitive radio. The non-cooperative games applied in UAV-aided wireless communications include zero-sum pursuit-evasion differential game, N-player normal form game, sub-modular game, anti-coordination game, Bayesian game, and evolutionary game.

Zero-sum Pursuit-evasion Differential Games: Differential games are a group of problems dealing with the control of objects, which are in conflict situations [137]. In these games, possibilities of players are modeled and analyzed by differential equations containing control vectors manipulated by players. Each player in a game can only use current information on the behavior of other players in choosing its control. The elements of an *N* player differential game include a continuous time interval, trajectory space, action space, a differential equation, and a set-valued function.

Zero-sum game [138] is a mathematical representation of a situation where the loss (or gain) of payoff of a player is precisely balanced by the gain (or loss) of payoff of the other player(s). If the total losses of players are subtracted, and the total gain are added, their sum will be will be zero. In zero-sum games, players have no common interest. For the zero-sum two-player game, a player chooses a strategy that maximizes its payoff matrix and minimizes the other player payoff matrix.

Pursuit-evasion game models a problem in which one group is chasing another group in a given environment [139]. For two player pursuit-evasion game, players are referred as pursuer and evader. The pursuer chases the evader, while the evader flees from the pursuer. If the pursuer and evader have controls $u_1(t)$ and $u_2(t)$, respectively, with state vector $x(t)$. Both, pursuer and evader have the same but, opposite sign cost functional, making the total reward zero, and thus, zero-sum game. The payoff function that the players try to maximize or

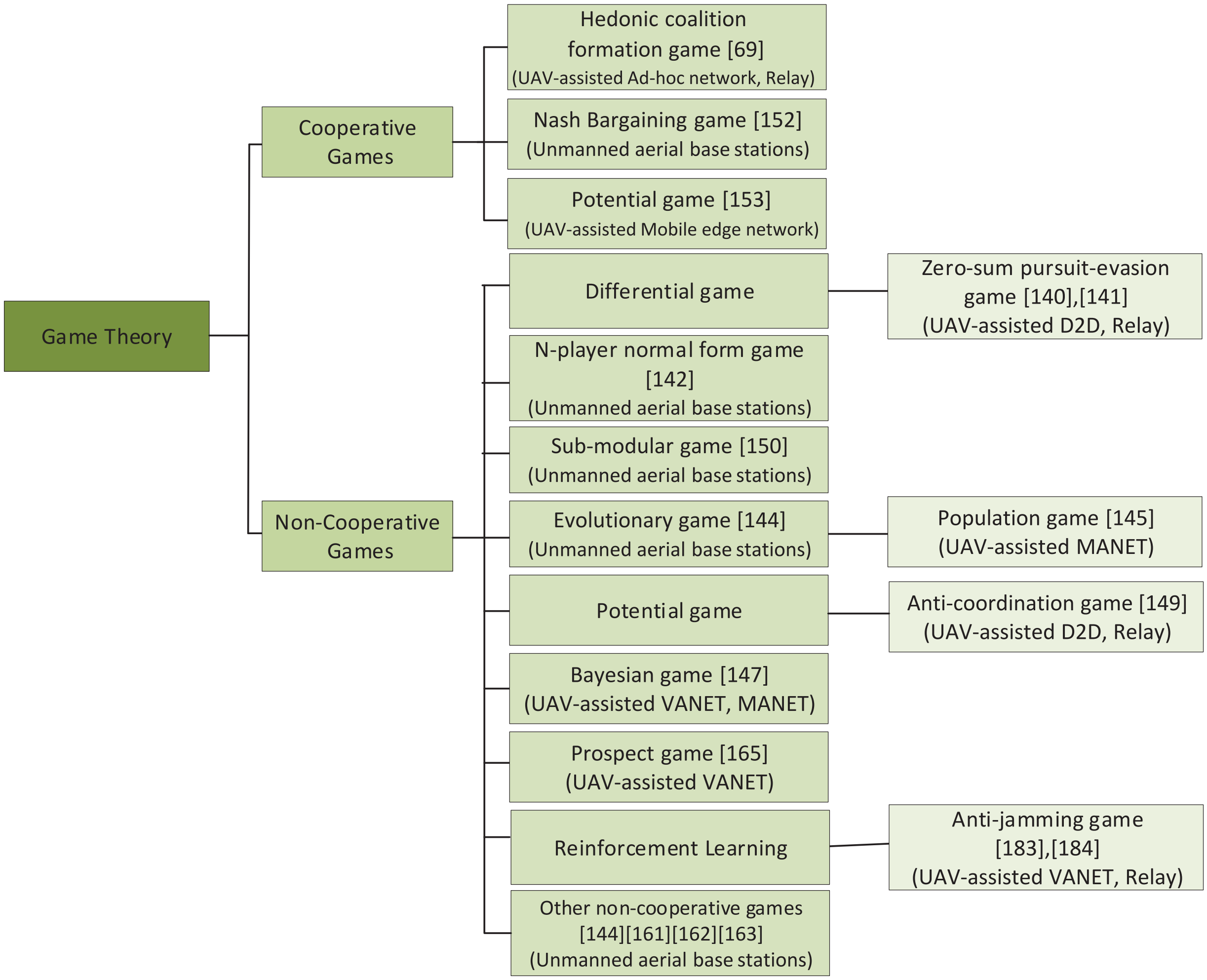

Fig. 9. Classification of current applied game-theoretic approaches in wireless communications with UAVs.

minimize the capture time (t_f) is given by

$$\pi(x(t), u_1(t), u_2(t)) = \int_0^{t_f} L(x(t), u_1(t), u_2(t))dt + G(x(t_f))$$

where L and G are final and running cost with values 1 and 0, respectively for the pursuit-evasion game. The outcome of the game obtained after the implementation of player's best strategies is called value function. In wireless communications with UAVs, zero-sum pursuit-evasion differential games are applied to protect the communication channel from malicious attacks [140] and for optimizing channel capacity [141] in UAV-based D2D and relay networks.

N-player Normal Form Games: A normal form is a description of a game, which represents the game by way of a matrix. In these games, each player chooses its own plan of actions and acts simultaneously without knowing the plan of actions of other players [142]. Each player then receives a utility value based on their joint actions. The assumption is that players have common knowledge of utilities that all players can receive. The work in [142], is a typical example of a non-cooperative normal-form game applied to find load balancing in wireless communications where UAVs are deployed as flying base stations.

Evolutionary Games and Population Dynamics: This type of games define game models in which players adopt their strategies through a process of trial and error in which they learn over time that some strategies work better than others [143]. The process is similar to natural selection used to determine how population evolves. In this model, the population is divided into sub-populations, and then members of sub-populations randomly play against each other. The sub-populations that will do well would grow, and those that did not do well would decrease. The process of improving populations based on the players' performance would be repeated indefinitely until the evolution converges to a stable state for each population, which would represent the best response for each agent. Evolutionary games have been utilized to control and coordinate unmanned aerial base stations in [144], and general UAV-based network in [145].

Bayesian Games: These are games in which information about other players' characteristics is incomplete. Specifically, in Bayesian games, the incompleteness of information implies that none of the player is sure of the type of information of the other players. The game provides a relaxed methodology to many of real-life situations where players have only partial information about the utility of relevant information [146]. Nash equilibrium in Bayesian game is formed based on the notion of best reply and is referred to as Bayesian equilibrium. In [147], Bayesian game is used as a tool to secure UAV-based vehicular network.

Anti-coordination Games: A game in which choosing the corresponding or same strategies creates a cost instead of a benefit is referred to as anti-coordination game [148]. The principal of the game is that, it is beneficial to both players if one of them yields, and if none of the players yields the results is costly to both, i.e., playing different strategy is beneficial to both players. For a two-player game, if the one yields, then the other player should not but if the first one does not yield, the other player should. The game is also known as a hawk-dove game and has more than one Nash equilibrium. Authors in [149], address the channel assignment problem in the combined UAV and D2D-based network by exploiting anti-coordination game.

Sub-modular Games: These are a particular type of none cooperative games in which NE always exists. The sub-modular functions are defined as follows. Let $N = \{1, \ldots, n\}$ be a ground set and $f : 2^N \rightarrow R$ a set function, where 2^N is the set of all subset of *N*. Then a set function *f* is sub-modular if $f(A) + f(B) \geq f(A \cap B) + f(A \cup B)$, $\forall A, B \subseteq N$. In other words, in a sub-modular game, when a player takes a lower action according to a defined order, the other players are better off if they also take a lower action. For the sub-modular game, neither convexity nor concavity assumption is required to guarantee Nash equilibrium existence. Sub-modular games have demonstrated to be useful in solving unmanned aerial base station energy-efficient problem [150].

2) Cooperative Games: These are structures in which players are allowed to form agreements as a group before choosing their actions [151]. The agreements formed can impact the strategic selections of players and their payoffs. Cooperative games are often analyzed through predictions on the coalitions that will be formed, actions that groups take jointly, and the resulting collective payoffs. The two elements of cooperative games are set of players N and characteristic function $v = 2^N \rightarrow \mathbb{R}$ that specify the value created by the subset of players in the game. The characteristic function describes the amount of collective utility that a set of player can obtain by forming a coalition. Examples of cooperative games that have been applied in UAV-assisted wireless communication are Hedonic coalition formation games [69] to optimize performance of UAV-based relay network, Nash bargaining games [152] to improve energy efficiency of flying aerial base stations, and potential differential games [153] to address offloading problem in UAV-assisted mobile edge network.

Potential Games: If the incentive of every player in changing its strategy can be represented using a single global function known as potential function, then the game is referred to as a potential game. In other words, the game is a potential game if and only if a potential function exists [154]. By definition, a function $P : S_1 \times \cdots \times S_n \rightarrow \mathbb{R}$ is a potential function for a game $G = (S_1, \ldots, S_n, p_i, \ldots, p_n)$, if $\forall i \in \{1, \ldots, n\} \forall s_{-i} \in S_{-i} \forall s_i, s_i' \in S_i$ and $p_i(s_i, s_{-i}) - p_i(s_i', s_{-i}) = p_i(s_i, s_{-i}) - p_i(s_i', s_{-i})$, where S_i is player *i*'s strategy and n is the number of players. The notions of potential game include exact potential, weighted potential, ordinal potential, best-response potential, and pseudo-potential [154]. In these games, each player has its own utility function depending on strategy, and individual player's utility function affects the change in global function in the exact amount. In potential games, because every player maximizes potential function, the existence of pure strategy Nash equilibrium is guaranteed.

Nash Bargaining Games: Nash bargaining games (NBGs) are used to model bargaining interactions among players. The bargaining problem was first introduced by John Nash in 1950 [155]. In NBG, players have mutual agreement for cooperation in order to attain higher payoff compared to a competitive option. In the game, each player demand a portion of some good, if sum of the proposals is no more than the total good, then both players get their demand. Otherwise, both get nothing. The solution to NBG is called Nash bargaining solution [156]. For *N*-player bargaining problem that satisfy all the conditions, there is a unique solution function, given by $u^* = \arg\max_{u_k > \overline{u}_k} \prod_{k=1}^{N} (u_k - \overline{u}_k)$. Where, u_k and $\overline{u}_k$ are payoffs of player k in case of cooperation and non-cooperation, respectively. When the payoff of a player *k* cannot achieve $\overline{u}_k$, the player will quit the cooperation. Because Nash bargaining solution has the property of fairness, the bargaining problem optimal solutions obtained using NBS are considered to be fair [156].

Hedonic Coalition Formation Games: Coalition formation games are cooperative games theory concepts. They consist of set *N* of players, and a set $\mathbb{C} \subseteq 2^N$ of possible coalitions, where 2^N is the power set of *N*. In these games, players form cooperation groups with a binding agreement to form a coalition which strengthens players' position in a game [157]. In coalition games, a group of players deliberately get together to jointly determine their action so that they can maximize their utility by cooperating with each other. The payoff of a coalition game will be specified by which group of players forms, and the collective strategy that the group takes. Then the joint payoff will be divided among all members of the coalition. Coalition games can be divided into three categories which are, coalition formation, canonical coalitional, and coalitional graph games [158]. The main feature of hedonic coalition formation game is that, the utility for each player is completely determined by the set of players in the coalition it belongs regardless of which other coalition may or may not be present [159]. In UAVs-assisted wireless communications, coalitions can be formed to optimize power consumption and therefore prolong network lifetime. The coalition games formulations are also suitable for solving problems in other UAV-assisted systmes such as video surveillance in wireless networks, monitoring and data collection in ad-hoc networks, and self-deployment of wireless mobile relays.

C. Leveraging Game Theory for UAV-Assisted Networks

The UAV-based networks possess unique characteristics such as high dynamics, easy deployment, flexibility in reconfiguration, complex operational environment, and high degree of autonomy, giving the network added benefits over terrestrial based networks. However, these unique properties introduce many new challenges that require advance techniques to address. Game theory is among the promising techniques for tackling some of the issues in the UAV-assisted network. There are numerous advantages of applying game theory, which create favorable conditions for researches in UAV-based wireless networks.

- The dynamic nature of UAVs introduces speed, direction, path, and power control problems in the network. Game theory comes as the right tool for addressing control problems such as power and motion control of UAVs in the network. Using game theory such as differential dynamic games, the UAVs can decide on the optimal velocity, placement, and power consumption for network optimal performance.
- Game theory such as reinforcement learning, evolution game, and mean field game allow network expansion. These games are perfect for UAV-based network, because they allow more UAVs to be removed or deployed on demand. Moreover, these games present distributed frameworks that provide flexibility and self-reconfiguration of the network.
- Future wireless networks including UAV-based networks are expected to be very dense. Massive number of UAVs carrying communication device can be deployed for surveillance, providing IoT services, support mobile devices in areas affected by catastrophic disasters, collecting and dismantling data in difficult to reach areas such as desert, oceans, thick forests, and high mountains. With huge number of nodes in the network, advanced game theory such as evolutionary games and mean field games comes in hand.
- Game theory provides the possibility for network nodes to cooperate or compete. In UAV-assisted networks, the UAVs can be designed to cooperate or to compete depending on the purpose so as to yield better performance. For example, using game theory UAVs can cooperatively collect and dismantle data, thus reduce unnecessary movement, minimize time for completing tasks, and minimize energy consumption. Similarly, using game theory, UAVs can be designed to compete in providing network coverage, to ensure reliability, availability, and quality of service to users.
- Compared to terrestrial networks, the UAV-based networks are faced with more decision to make at the same instant. Examples of such decisions are, angle and directions to take, speed to move with, amount of power to transmit, their optimal placement and altitude, intruders detection, and others. As a tool to facilitate decision making, game theory can be the right mechanism for multiple decision making process in the network.
- Wireless communication with UAVs requires extensive amount of information exchange. Constant communication with ground control stations, continuous communication with other flying UAVs and devices to avoid collision, and communication with other ground devices not only consume huge amount of power but also leads to severe interference. Game theory such MFG which need information only at the initial stage, and Bayesian games which require partial information, provide an opportunity for UAVs to minimize the exchange of information, thus reducing energy consumptions and interference.
- Resource and interference challenges are common to wireless networks, but are more acute in UAV-based networks due to their dynamic nature and LoS communications. Game theory is considered to be the right tool that can address these issues in UAV-assisted networks.

The current game theoretic approaches as applied to the wireless communications with UAVs are summarized in Table III. The table provides the game models, key concepts, and a example scenarios where they can be applicable.

IV. Applications of Game Theory in UAV-Aided Wireless Communications

Game theory has shown many possible applications in wireless communication with UAVs. In this section we present challenges that have so far being addressed using game theoretic approach. We provide a brief discussion on the problem for a general UAV-assisted network, and then survey works that utilize game theory to address that particular issue. We also present the pros and cons of the applied game theory and propose open research issues.

A. Optimal Height and Coverage

The UAV height has an impact on the coverage performance, service availability, and link reliability over the area that it provides service. When the UAVs are appropriately positioned, the number of UAVs required to provide coverage can be significantly reduced which result in a reduction of resources and time required to establish the network [61]. There is also a relationship between UAVs' optimal altitude, especial for low altitude UAVs and maximum coverage of the area over which it provides coverage [21]. Fig. 10 shows similar UAVs carrying the same wireless transceivers and have the same antenna with a fixed beam width θ, at different altitudes cover the ground areas proportional to their height. Therefore, proper mechanisms are needed for positioning of UAVs in order to provide maximum coverage to the ground nodes with satisfactory quality.

In [161], a non-cooperative game is used to find the optimal placement of two UAVs that provide backbone communications to a group of ground mobiles. In this game model UAVs are considered as a set of players, $P = \{p_1, p_2 \dots p_n\}$ whose strategies are the set of possible next locations, $S = \{s_a, s_b, s_c \dots s_m\}$. The payoff of each player, $M = \{\mu_1, \mu_2\}$ is a number of ground mobiles uniquely covered by each UAV within the constraints of undulating terrain and limited radio frequency power. In this game, UAVs are considered to circulate in a given path and have seven possible moves defined as vertices. The UAV can choose to continue using the same path or move to any of the six adjacent vertices of its hexagonal area. The other two possible moves are downward and upward movements. A Nash equilibrium (NE) is obtained by searching for the best response in the bimatrix. The algorithm

TABLE III
SUMMARY OF THE TYPES OF GAMES APPLIED IN UAV-AIDED WIRELESS COMMUNICATIONS

Game model	Key concept	Example Network Scenario	References
Hedonic coalition formation game	Forming cooperation with binding agreements to form coalitions	Data collection, video surveillance in wireless networks, Network monitoring, and Mobile relays	[69]
Zero-sum pursuit-evasion differential games	Evading an attack from the jammer that wants to jam UAV communication channel and optimizing communication channel capacity	UAV-based relay communication network in the presence of jamming UAV	[140], [147], [160]
N-player normal form game	Players take action simultaneously without knowing the action of other players	Unmanned aerial base stations and WiFi access point balancing load between themselves to ensure maximum throughput for all users in a UAV-assisted LTE-U/WiFi heterogeneous network.	[142]
Sub-modular game	If a player takes lower action according to the defined rules; the other players are better off taking a lower action too	Aerial base stations competing to maximize their encounter rate by strategically choosing their beaconing period	[150]
Non-cooperative games	Finding the best individual strategy to maximize individual payoff	Communications UAVs competitively relocated to maximize coverage of ground mobiles	[144], [161]–[163]
Population games	Players adopt their strategies by trial and error as they learn over time	Group of communicating UAVs coordinated and controlled to perform a specific tasks such as data collection	[145]
Bayesian game	Player adopt strategies while having partial information about the utility of the associated data.	UAV-aided VANET where UAVs forward messages in a safety-oriented vehicular network	[147]
Nash bargaining game	Each player demand a portion of the available resource, if sum of the proposals is no more than the available resource, then both players get their demand or else both get nothing.	Unmanned aerial base stations strategically cooperate to choose their probing period to maximize their encounter rate	[152]
Anti-coordination game	Both players benefit only if they choose different strategies, and very costly otherwise	UAV-assisted D2D-enabled network where channel assignment needs to be optimized to minimize interference	[149]
Prospect game	Players make decisions under uncertainty or risks	UAV-based vehicular networks where UAVs choose their transmit power on multiple radio channels to resist smart attacks	[164], [165]
Potential game	Each player has an individual payoff function depending on the strategy chosen	UAVs in mobile edge computing facilitating offloading process of intensive computation tasks to an cloud/edge server	[153]

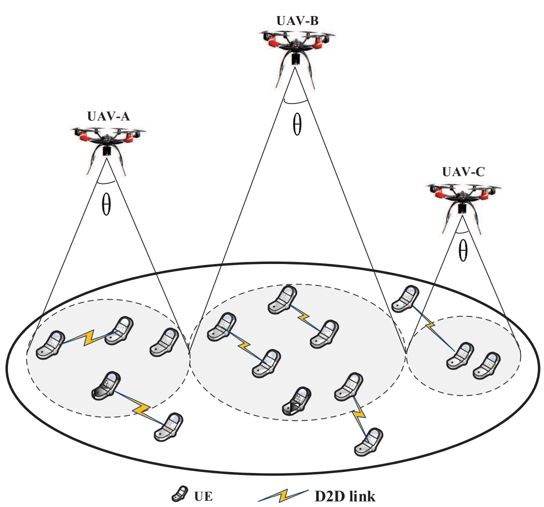

Fig. 10. A scenario where similar UAVs cover ground areas proportional to their height.

described in [166] is used to determine the optimum location of a single UAV based on estimates of the locations of mobiles, then calculate the number of mobiles that can uniquely be supported by each UAV at any particular position. Complete information about strategies and payoffs is derived using time-stamped broadcasts from mobiles and UAVs. After simulations, the results indicate that the two UAV engaged in a non-cooperative competition provide better coverage than a single circling UAV.

As an extension to [161], authors in [162] use the concept of a non-cooperative technique for optimizing location of UAVs in a 3-UAV system. The game-theoretic approach requires that each UAV attempt to maximize its support of mobiles, taking into consideration the payoff and strategy of other UAVs. In this game, each UAV has a set of strategies, which are the next move choices. Each player's utility that corresponds to its selected strategies is calculated in three stages process. First by calculating the link budget of the RF power required to provide the backbone network between UAVs. Secondly, payoff was calculated by the link budgets for all mobiles from each UAV in all locations that map to the strategy of that UAV. Lastly, payoff was calculated by weighing other options such as retaining, adding or dropping a mobile. By finding one NE from the *n*-matrix, UAVs choose their strategies simultaneously. The numerical results obtained demonstrate the usefulness of the non-cooperative game in coordinating movements of the UAV for optimal network coverage. The results show that three UAVs outperform two UAVs in terms of coverage.

The pitfall of these games is that only a small number of UAVs (i.e., two UAVs in [161] and three UAVs in [162]) are considered in computations. This is due to the increase in utility function computational complexity as the number of UAV grows. The techniques also fail to account for the effect that might happen to the quality of the signal received by users when UAVs change altitudes. Moreover, there still a need to take into consideration different speeds of UAVs, and investigate if there is in any effect on the coverage. In [161], it is mentioned that UAVs coordination has the potential to minimize interference, however, no results provided to show how much interference can be minimized. Since there is a trade-off between the connectivity and achievable area for coverage [167], a comprehensive study on the network performance is needed when game theory based technique is used for finding optimal coverage.

In this subsection, the problem of maximum coverage and optimal height in UAV-assisted network is discussed. The network scenario, game formulation, and results are studied. The results of non-cooperative games presented indicate that the games offer useful techniques for coordinating movement of UAVs on a given coverage area. The techniques have significant effect on the network performance by providing good coverage, and optimize the use of available energy. Moreover, the non-cooperative games allow networks to operate without central planning agent and with high level of autonomy. The games discussed in this subsection use similar approach, in which UAVs are given a set of choice for their next moves, and choices are made by finding NE. The techniques show improvement in performance when three UAVs are used compared to two UAV system, but the two-UAVs system converges faster to equilibrium due to less exchange of information between UAVs. Although the games demonstrated good performance, there are still shortcomings and open research areas as discussed in the preceding paragraph.

B. UAV Coordination and Mobility Control

To support billions of devices, a large number of UAVs are expected to be deployed in order to assist the network in the coming years. Advanced methods for controlling and coordinating UAVs become necessary. Placing an UAV at an optimal fixed altitude and angle of elevation can provide maximum coverage [21]. However, the dynamics of UAVs can be leveraged to improve the performance of wireless network [168], [169]. The motion of UAVs can be controlled to improve capacity of the link and to maximize throughput [170]–[172]. Fig. 11 reveals the scenario where massive drones are deployed for different purposes. In such a network, to avoid collisions and maximizing system throughput, a proper coordination and motion control schemes are necessary.

The comparison between evolutionary algorithms (EA) and noncooperative game mechanism for coordinating UAVs in finding their optimal location is presented in [144]. The scenario where a small group of UAVs is deployed to provide network coverage backbone for an extensive number of unpredictably mobiles is considered. The UAVs, as players moving in hexagonal cells airspace, use their next move choice as the competitive strategy. The UAVs' purpose is to choose the best moving strategy to maximize mobile coverage. For the non-cooperative game, authors used an algorithm derived in [173] for finding Nash equilibrium, which would always find a mixed strategy Nash equilibrium, and usable for games where the number of players is greater or equal to two. For the evolutionary game, evolutionary algorithms are used to evolve collaboratively flying maneuverer. In this mechanism, master UAV is chosen, whose primary function is to run the algorithm and distribute solution which contains a set of flying instructions for every UAV. The distributed instructions allow UAV maneuvering according to three defined consecutive flying segments. The comparison outcome of the two mechanisms under the same scenario and conditions indicates that both methods allow the UAVs to position themselves to have maximum coverage. The non-cooperative game strategy equally distributes the load among UAVs on covering mobiles resulting in a power balanced mission. This can offer advantages when managing radio frequency interference between the platforms. In this comparison, the EA demonstrated to converge faster to equilibrium compared to no-cooperative game.

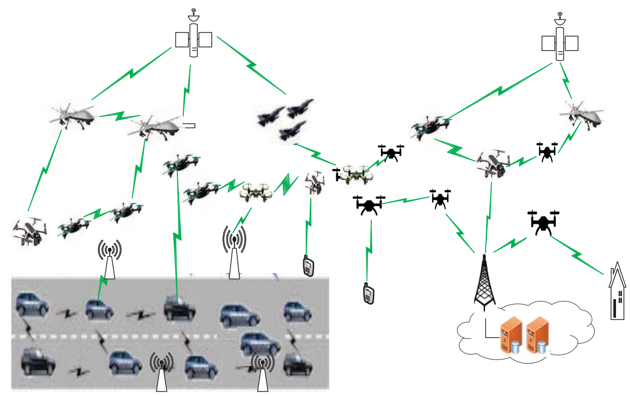

Fig. 11. A scenario where massive UAVs are deployed to perform various tasks.

In [145], the UAV control scheme using population game is proposed. Authors present evolutionary game under time-varying communication graph to solve the UAVs' distributed formation problem. In this game, UAVs who are the players, have partial information about the whole set of UAVs. The set of player $A = 1, 2 \ldots, N$, where $N \geq 2$ with a leader symbolized as $l \in A$, that influences decisions of all other agents, referred to as followers and denoted as $F = A \backslash \{l\}$. The communication network is considered to be undirected graph and is denoted by $G(t) = (A, \varepsilon(t), \mathrm{A}(t))$, where A is a set of node corresponding to each agent, $\varepsilon(t)$ is the link set of the communication network, and $\mathrm{A}(t)$ represents the adjacency matrix. In this game, the leader $l \in A$ use already established trajectories and contains a spacial reference for the followers $i \in F$ to perform the formation. The population game considers different populations in a very large number of decision makers represented as $D = \{x, y, z, \theta\}$ and $A = 1, 2 \ldots, N$ as the set of available strategies for all $d \in D$. $F = A \backslash \{l\}$ is a subset of strategies and $l \in A$ is a fiction strategy. x, y, and z are the coordinates while (θ) represents the rotation. The definitions for achieving convergence to Nash equilibriums were given. The novel distributed formation control proposed has shown to achieve the formation using decentralized communication structure among UAVs.

To improve system throughput, authors in [163] proposed distributed mobility control algorithm based on game theory to guide the movement of the drone base stations (DBSs) moving continuously over an area where terrestrial infrastructure is destroyed by a disaster. Using the designed algorithms, DBSs continuously adapt the directions by which they move in order to provide high-quality service for users moving on the ground. The game theory-based algorithm was developed, in which the direction selection of the DBS is formulated as a non-cooperative game. The turning angles for each DBS are considered as actions, and the utility is defined using the spectral efficiency of a particular DBS. In this algorithm, at first, all DBSs choose a random direction from their set of actions and then finds their best response while considering other drones' action that maximizes the utility function. The game is played, and the decisions leading to the Nash equilibrium (NE) are adopted by DBSs to update their directions. Regardless of the number of DBSs and users, the simulation results have demonstrated that the proposed mobility control algorithms can improve the average packet throughput by 82% and the 5th-percentile packet throughput by 430% compared to a scenario where DBSs hover over fixed locations.

The proposed game-theoretic algorithms for coordination and mobility control of UAVs have proved to be very useful in advancing wireless communications. The algorithms in [163] and [145] allow a large number of UAVs to be deployed, therefore very suitable for large-scale networks. In [163], the algorithm allows network growth by integrating new agents, the network's shapes can be reconfigured dynamically along the time, and network agents have partial knowledge about the network, thus very potential for future ever growing dynamic wireless networks. However, the distributed mobility control algorithm can further be improved by designing the leader to move according to the movement pattern of ground mobile devices (e.g., sensors, cars, and smartphone) rather than following the pre-established trajectory, thus allowing the algorithm to be used for UAV-based cellular and sensor networks. Designing the leader to move according to ground mobiles will also minimize unnecessary movements, thus optimize UAVs' energy consumptions. Moreover, the algorithm can take into account obstacles to avoid collision and improve UAVs' security. In [145], the game theoretic scheme enhanced network throughput by reducing UAV-base station distance from users and improve line of sight communications. The designed algorithm also prevents UAVs to move close to each other, thus avoid collisions. However, more studies can be done to allow UAVs to move in three dimensions to improve coverage and throughput.

Four game theory applied to address coordination and mobility control problems are discussed in this subsection. Two games, the evolutionary and a non-cooperative game approaches for controlling two unmanned aerial base stations were studied and compared in [144]. Both approaches have shown to improve system adaptive coverage, minimize information exchange between UAVs, provided high degree of autonomy, and optimized UAV's energy consumption throughout the duration of mission. While the evolutionary game proved to converge faster to the equilibrium due to their flexibility, the non-cooperative on the other hand despite requiring more time to reach equilibrium has shown to be consistence in its coverage that is distributed evenly between UAVs. This subsection also presented a distributed formation control technique based on population games under time-varying communication graphs for a multi-UAV system structured in a leader-follower manner [145]. The proposed control technique can deal with system formation objectives and can conveniently vary the information sharing network while maintaining the stability and connection of the agents. The technique allows the dynamic incorporation or removal of an agent to and from the formation without affecting other agents' controllers. Moreover, this section presents a non-cooperative game theory approach to address mobility of flying drone base stations to improve network throughput [163]. Using the proposed mobility algorithm, the base stations are allowed to fly freely in the entire network area resulting in significant improved system performance in terms of throughput.

C. Performance Optimization

In the future, wireless communication is expected to present a complex and dynamic environment. With the continuous increase in traffic, size, applications, and services in the wireless systems, mechanisms for organizing and allocating tasks such as data transmission and collection are needed. As shown in Fig. 12, UAVs will be deployed to perform various tasks in the network such as relaying, providing coverage, and carrying and disseminating data. Some of UAVs will work cooperatively, and other independently. These flying vehicles might belong to different companies, individuals, or governments. To optimize performance, special methods for organizing and assigning task will be required. Game theory can be used as a method for autonomously task allocation among UAVs to enhance performance.

For example, in [69], a novel game strategy for task allocation among UAV-assisted wireless communication network is introduced. The task allocation problem is modeled as hedonic coalition formation game between UAVs and tasks. In this cooperative game, a number of UAVs controlled by a central base station and belong to a single operator are required to collect data from arbitrarily located areas and then wirelessly transmit the collected information to a common receiver. Tasks represent queues of data packets that need collection and wireless transmission by a UAV to a centralized receiver. The set of UAVs is denoted as $M = \{1, \ldots, M\}$ while tasks set is denoted as $T = \{1, \ldots, T\}$. The set of both UAVs and tasks is detonated as $N = M \cup T$ and it is always assumed that $T > M$. Each formed coalition $S \subseteq N$ is mapped to a polling system that comprises of a number of UAVs that collect packets from various tasks continually. In a coalition, the UAV can act either as a relay to enhance data packets transmission or as a collector that move between the different tasks collecting the packet data in the coalition.

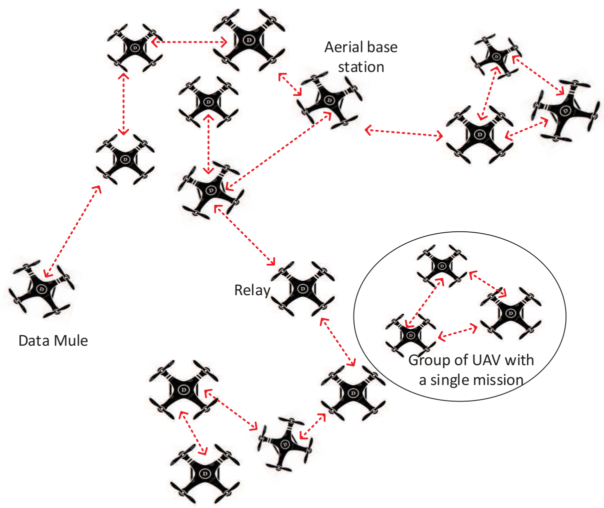

Fig. 12. Example of a scenario where UAVs are deployed for different functions in a network.

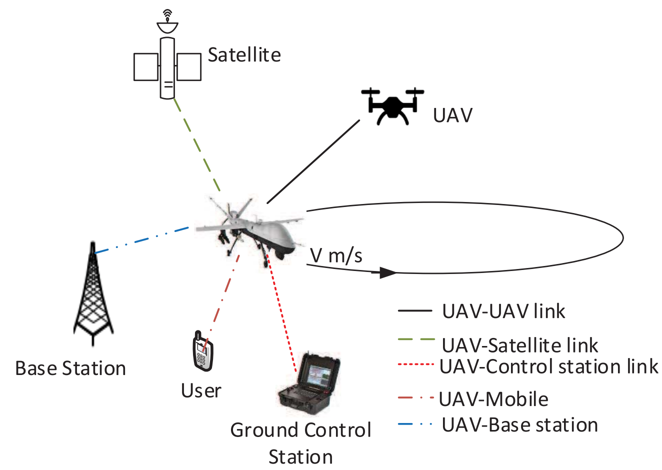

Fig. 13. Communications links that contribute to the energy consumptions in a typical communicating UAV.

With the average throughput L_s for coalition S, mean waiting time at task i of $\overline{W_i}$ and the ratio of task arrival rate to the link transmission capacity with which the task is being served ρ_i, the total revenue achieved by the coalition is given by the function,

$$v(S) = \begin{cases} \delta \frac{L_S^B}{\left(\sum\limits_{i \in S \cap T} \rho_i \overline{W}_i\right)^{(1-\beta)}}, & \text{if } \rho_S < 0 \text{ and } |S| > 1, \\ 0, & \text{Otherwise,} \end{cases}$$

where $\beta \in (0, 1)$ is the throughput delay tradeoff parameter and δ is the price per unit power that the network offers to a coalition. Consequently, the utility of a player is given by $x_i^S = \frac{v(S)}{|S|}$. In addition, authors proposed an algorithm that allows the UAV to leave or join the coalitions depending upon their inclinations which catch the tradeoff between the delay and effective throughput achieved by the coalition. The proposed algorithm allows the tasks and UAVs to organize themselves into independent coalitions and improve network performance.

The hedonic coalition formation game in [69] yields a better performance of more than 30.26% in average compared to equal allocation of task strategy. The algorithm allows network self-adapting by allowing UAVs to leave or join any coalition and also switch between being collectors or relays, thus greatly improve packet success rate of transmission at minimum delays. However, the algorithm does not take into account the movement and speed of the tasks (i.e., mobiles) in the network. In addition, due to the dynamic nature of the mobiles, UAVs can also be allowed to re-join the coalition that it has previously left. Further investigation can be done to compare results when the motion of the mobiles is accounted for and when if UAVs are allowed to revisit the former coalition.

In this subsection, the problem of collecting data from random located nodes and transmitting this data to a common receiver wirelessly using UAVs is studied. The task allocation problem is modelled as a hedonic coalition formation game between agents in the networks. The system formation and the cooperative game mechanism are studied. The results showed the algorithm allows the agent to self-organize into independent coalitions, while improving the system performance in terms of throughput and delays. Possible open research areas are also presented to improve upon the proposed algorithm.

D. Energy Saving and Power Optimization

The operational and performance duration of UAVs are basically restricted by the limited onboard energy. The problem becomes worst when UAVs are used for communications reasons. This is because, in wireless communications, UAVs will need energy for establishing communication with other UAVs, satellites, ground nodes, and terrestrial communication infrastructures in addition to the energy consumed due to the payload, motion, and communication with ground control stations. Fig. 13 presents possible links and motions that drains UAVs' energy. The propulsion power consumption for maintaining the UAV aloft and supporting its mobility is usually much higher than the conventional energy expenditure communication-related functions, such as communication circuits and signal transmission (e.g., hundreds of watts versus a few watts) [54]. Therefore, it is critical to address both, the energy consumption due to communications and motions of UAVs.

Improvement in the battery life, the use of solar energy and other means of energy storage have been some of the methods used to improve UAVs' energy capacity. From the operational point of view, the problem can be addressed by introducing energy efficiency operations so as to reduce UAVs' unnecessary energy consumption during the operation. To manage and minimize the energy consumed in the UAV-based wireless communications networks while satisfying communications requirements, game theory approaches have been proposed [150], [161], [162].

As efficient means of energy optimization, authors in [150] applied a non-cooperative sub-modular game for beaconing periods scheduling. A periodic beaconing for UAV and passive scanning for mobiles is proposed. In this sub-modular game, two UAVs, i and j acting as aerial base stations are considered as players who compete to maximize their coverage probability of mobiles in the area of interest. During the competition, if in one of its beaconing periods, UAVi meets the mobile first, then it succeeds. Otherwise, if UAVj encounter mobile users first, then UAVi will succeed when UAVj encounters a mobile during an idle period of its activity schedule. The scheduling of beaconing periods is modeled as $G = \{N, \{A_{\{i \in N\}}\}, \{u_{\{i \in N\}}\}\}$ where N stands for set of UAV with action set $A_i = [0, T]$. With τ_i and τ_j comprised between zero and period *T*, being the beaconing period durations of UAV i and j, respectively. The payoff of the UAV is calculated as the trade-off between encounter probability and energy consumption. The utility function of UAVi is represented as,

$$u_i(\tau_i, \tau_j) = P_s^i(\tau_i, \tau_j) - \frac{(C_b \tau_i + C_s)}{m}$$

where $P_s^i(\tau_i, \tau_j)$ is the encounter probability rate, and m is the encounter deadline, l is the number of cycles. C_b and C_s are the energy cost per slot for sending beacons and switching the transceiver state respectively. With the provided learning framework UAVs are allowed to reach equilibrium. Using the properties of sub-modular games, the uniqueness and existence of the Nash equilibrium were checked. The Nash seeking algorithm was proposed and the numerical results obtained after simulations. The results show that at the equilibrium point, UAVs efficiently optimize their energy consumption and at the same time maximize the possibility of contacting mobile users on the ground. For instance, at an encounter rate between 1.3 and 5, using strategic beaconing the energy efficiency of UAVs increased from 1.59 to 5.64 folds compared to always beaconing strategy.

In [161], the non-cooperative game that uses time stamped broadcasts from UAVs and mobiles to derive all the information about strategies and payoffs is used. As a result, the information exchange required to coordinate and allow both UAV to attain the same solution with minimum coordination and high autonomy is minimizes. To give the algorithm some level of tolerance to the missing or delayed broadcast messages, the location estimates is used. Numerical results indicate that two competing UAVs provide altogether better coverage and improved total power efficiency by allowing the distribution of power across the two UAVs. The power to support inter-UAV link and mobiles on the ground for two competing UAVs is less than one-third of that required by single UAV.

The authors in [162], have proposed a non-cooperative game for UAV location optimization in order to maximize its support for mobiles. The proposed game offers a useful method for coordinating UAV's movement on area coverage mission without a central planning agency. The communication-equipped UAV demonstrated to provide excellent coverage while using the available power efficiently by optimizing its movements.

The non-cooperative game theoretic approaches in [150], [161], [162] have provided UAVs in the network with the capability to act autonomously and significantly improve energy consumption compared to the non-game theory techniques. However, the proposed schemes in [150] and [161] only consider the networks of two UAVs, and three UAVs in [162], hence not suitable for large networks. Therefore, a more suitable mechanism for large network and that allow network scalability is needed. Moreover, since the designed utility function in [150] is proved to be compact, continuous and concave, there is an opportunity for it to be applied to optimize energy of similar network using cooperative Nash bargaining game [174], which has been used in other networks for energy-efficient optimization. The analysis and comparison between the cooperative and non-cooperative games can be provided to find a technique that gives optimal results.

In [150], [161], [162], only communication-related power consumption has been addressed without considering large amount of power consumed due to the motion of UAVs. These games will have great impact to the overall power consumption of the network if the number of communication links is huge. A typical example will be when UAV-base station is used to provide coverage to a large number of users. However, if the number of communication links is small, there is a need to for alternatives that will take into consideration motion related power consumption. One basic alternative is to use fixed-wing UAVs, because their power consumption due to flying in the air is significantly less compared to rotary-wing UAVs. Using game theory, advanced techniques such as mean field game (MFG) can be used to address the problem. MFG can control not only the power of UAVs but also their velocity [175]. With MFG, UAVs can control their vertical and horizontal motion to minimize power consumption and interference, thus significantly extend the flying time. More discussion on MFG is given in Section V.

Due to system dynamic nature and the use of energy limited batteries, energy optimization problem is critical in UAVs communication networks. Three game theory proposed to address energy challenge are surveyed in this subsection. As an efficient method of energy consumption optimization, a sub-module game is utilized to deal with the activity scheduling of competing unmanned aerial small cells. The proposed distributed mechanism allows each UAV to reach its equilibrium beaconing strategy, maximize its probability to contact users on the ground while optimizing their power consumption efficiently. Moreover, the non-cooperative games applied to improve ground coverage while optimizing their energy consumption are presented in this section. To provide open research areas, the achievements and shortcomings of the studied games such as failing to address the energy consumed due to mechanical movements of UAVs are also discussed.

E. Capacity Maximization

The 5G network will be characterized by high capacity [176]. Deploying UAVs for wireless network will greatly improve coverage and significantly contribute to meet high network capacity demand [38], [121]. The UAV-based network can be optimized to further boost network capacity. For example, the evaluation of aerial LTE base-stations capacity is investigated in [177]. In wireless networks, the key parameter that defines the communication system performance is the channel capacity [178]. It is the highest rate limit at which information can be transmitted over a communication channel with an arbitrarily low probability of error. Enhancing network channel capacity can significantly improve quality of communication.

A zero-sum non-cooperative pursuit-evasion game posed as a capacity game in a UAV-aided communication system is presented in [141] and [160]. The game is modeled by considering two UAVs and a large number of relays. The two UAVs are considered as an evader and communicator. An evader tries to jam the communication between the communicator and relay nodes in the communication system. In this model, the communicator and relays are on different planes separated by distance $\in$. The capacity for the two relays is formulated using Shannons' capacity formula. The total capacity C_t, is computed as the sum of all the capacities of relays. The strategy of a jammer is to minimize the capacity while the UAVs' strategy is to move away from the jammer to maximize its channel capacity. The payoff is formulated as a function of position vector, probability function, and capacity.

After error minimization, simulations of a simplified form of the utility is done. With the designed dynamics and conditions, the game is solved using Isaacs method [137] to obtain optimal control. The purpose of the game is to minimize signal to noise ratio threshold. The obtained results show that the jammer always win the game.

There are still a number of problems that can be studied to improve upon the proposed game theory in [141] and [160]. As obtained results indicated, regardless of the optimal trajectories used for simulations, the jammer wins the game, bringing the capacity to zero. Thus, designing algorithm that provides higher sensitivity to allow communicator detect the jammer, make decisions, and take actions faster will be necessary. The algorithm that can also equip the communicator with the ability to accelerate and decelerate in avoiding the jammer will provide better results. In addition, rather than just considering two UAVs, a mechanism that can accommodate larger number of UAVs (jammer and communicators) have to be designed.

This subsection presents a zero-sum non-cooperative pursuit-evasion differential game. The proposed communication model and game strategies are studied. The problem is formulated in terms of optimizing system capacity and is solved using a set of Isaacs differential equations. The approach proposed can be extended to other security games such as network intruders. The shortcoming of the proposed game and open research areas are recommended in this subsection.

F. Security

UAV-aided networks are exposed to attacks that could cause an enormous amount of loss regarding money, reputation and data confidentiality. There are both physical and communication-related attacks that can occur to an operating UAVs [179], [180]. Represented in Fig. 14, are three possible security risks for UAVs. A physical attacker, collisions with other flying objects or obstacles, and communication intruder are the potential security risks to UAVs. Some of the attack

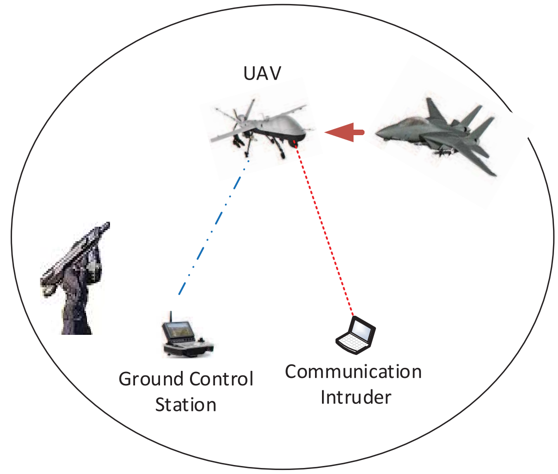

Fig. 14. Possible UAV security threats.

techniques are password theft, trojan horse virus, Man-In-The-Middle (MITM) attacks, Wireshark, and distributed denial of service (DDOS) attacks [181], [182]. For instance, in a UAV-based communication system, attackers can jam the communication between the UAV and controller, take control of a targeted UAV and dispatch different sorts of attacks, such as GPS spoofing. Hence, effective security mechanisms for detecting and protecting such networks against attackers are crucial.

Because of its ability to deal with problems where multiple entities with contradictory objectives are involved, game theory techniques can be applied to model and analyze wireless network security issues. The work in [140], proposed a differential game theoretic approach for computing optimal strategies which can be used by communicating UAVs to evade an attack from an aerial jammer on the communication channel. Three UAVs are considered in system model, a receiver, transmitter, and an aerial jammer. Jammer tries to jam the communications between two communicating UAVs. In this model, the metric used is the ratio of the jamming power to the signal power, i.e., $\frac{D_{TR}}{D_{JR}}$, where D_{TR} and D_{JR} are the Euclidean distance between transmitter and receiver, and between jammer and transmitter respectively. The purpose of the jammer is to raise the ratio above a certain threshold η. UAVs are assumed to be kinematics system and move at a constant altitude, thus the dynamics are not considered. Two problems were formulated as summarized in Fig. 15. First, by considering that the two UAVs are not communicating in the presence of a jammer at the beginning. In this problem, jammer seeks to maximize the time it can jam the communication, whereas the communicating UAVs aim to minimize the time that communication remain jammed. The game will end at the first moment at which the two UAVs are able to communicate. The second problem considers that UAVs communicate in the presence of a jammer at the beginning. While the jammer seeks to minimize the time in which it can jam the channel, the two UAVs seeks to maximize the time for which their communication channel remains operable. The termination of the game will happen at the first instant at which UAVs are about to lose communication. The problem was formulated as a zero-sum

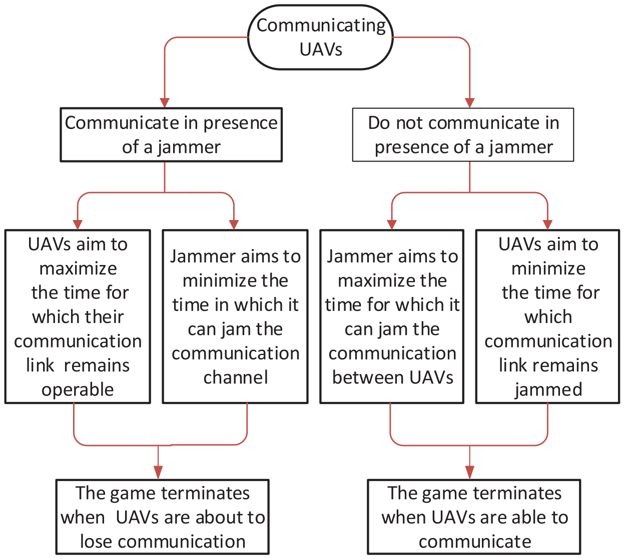

Fig. 15. Pursuit-evasion game formulation.

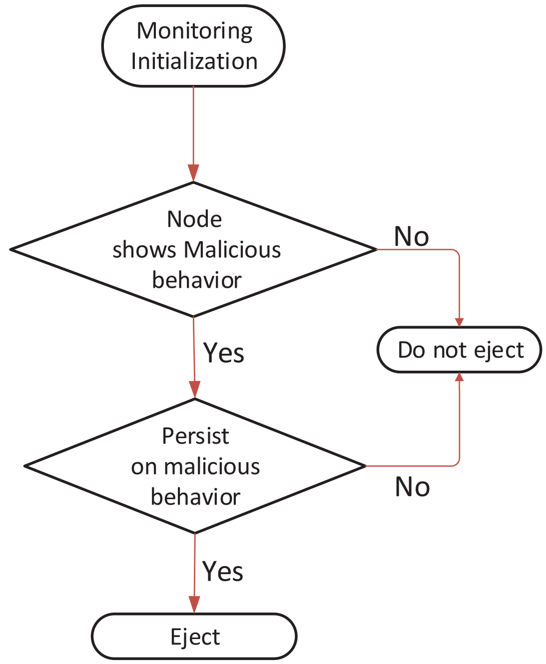

Fig. 16. Flow chart showing the process of detecting and ejecting malicious node in a communication system.

pursuit-evasion game and used Isaacs approach [137] to derive conditions needed to obtain equations that govern the saddle point strategies of the players. The termination time of the game is used as the cost function. Then the simulation of the differential equation governing trajectories and optimal control is done to demonstrate the effectiveness of the proposed method.

To protect the UAV-aided vehicular network against external and internal intruders, authors in [147] designed the intrusion detection system (IDS) and the intrusion ejection system (IES). IDS is designed for monitoring the network while the IES is for ejection of the node that is expected to instigate an attack. The system of clustered vehicles exchanging information through UAV-based relay to minimized delay and achieve better delivery ratio is modeled. The authors formulated two security problems, detection of intrusion and ejection of attacker as Bayesian game.

The first game involves two players, IDS agent and the attacker denoted as J_{IDS} and $J_{attacker}$, respectively. The strategies of IDS are as follows; the UAV_{i-IDS} which is enabled with JDS, monitor or awaits vehicle cluster head (CH_j), the CH_{j-IDS} which is enabled with JDS, monitors or awaits both, its cluster member (CM_k) and UAV_i, and the CM_{k-IDS} enabled with JDS, monitors or awaits CH_j. The attackers' strategy is to act maliciously or normal against UAV*i*, CH*j*, and CM_k. The set of profit (Q'_{ji}, Q_{ji}) gained by player J_{IDS} and $J_{attacker}$, respectively is formulated according to the strategies under four conditions. First, when IDS does not carry out monitoring process and attacker act maliciously. Second, when IDS does the monitoring process and attacker act maliciously. Third, when IDS does not carry out monitoring process and attacker act normally. And lastly, when IDS launches monitoring process and attacker act normally. Then the optimal solution defined as Bayesian Nash equilibrium (BNE) is determined as the average profit gained from the game. In this game, the IDS tries to maximize while an attacker wants to minimize the value of the gained profit. Hence the equilibrium point is achieved by upper $(\overline{B_{IDS}}, \overline{B_{attac\,\mathrm{ker}}})$ and lower $(\underline{B_{IDS}}, \underline{B_{attac\,\mathrm{ker}}})$ boundaries of the gain value of the game. Therefore, the BNE is given by

$$BNE = (\overline{B_{IDS}} = \underline{B_{IDS}}, \overline{B_{attac\,\mathrm{ker}}} = \underline{B_{attac\,\mathrm{ker}}})$$

The second game is between the IES, J_{IES} and suspicious nodes, J_{node}. In this game, when the node is categorized as an attacker by IES, it will first change its future state to either transitory or permanent. Similarly, the IES strategies are as follows; the UAV_{i-IES} which is enabled with IES eject (or not) vehicle cluster head (CH_j), the (CH_{j-IES}) also eject (or not) both cluster member (CM_k) and UAV_i, and the CM_{k-IES} strategy is to eject (or not) CH_j. The suspicious node strategy is to act as an attacker or normal. Like the first game, the set of profit (Q'_{ji}, Q_{ji}) is formulated according to three conditions, when J_{IES} does not eject and suspicions node is an attacker, when J_{IES} eject and the suspicions node is an attacker, and when J_{IES} categorize a node as an attacker and the suspected node act normal. The average IES gain point and suspected node gained point were defined and the BNE is formulated by using maximum and minimum values. The performance of this approach based on the concept of Nash Equilibrium has shown to incur a low signal overhead in detecting lethal attacks with great accuracy.

The process of detecting and ejecting malicious node is summarized in a flow chart given in Fig. 16. The IDS initialization will start system monitoring to detect nodes that behave maliciously. The persistence of suspected malicious of misbehaving will then be checked. If the node stops misbehaving will not be ejected but if persist misbehaving will be considered as an attacker. The attacker will be ejected and miss-communicated by the IES.

In [183] and [184], because UAVs can establish a line of sight links and smaller path loss exponents, they are deployed as relays to improve anti-jamming communication of VANETs. UAVs are used to relay vehicles message to improve signal-to-interference-plus-noise-ratio (SINR) of vehicles' signals, and thus reduce the bit-error-rate (BER) of the vehicle message, especially if the serving road side units are blocked by jammers and/or interference. In this network, the interaction between jammer and UAV is formulated as anti-jamming relay game to investigate the resistance against smart jamming in the UAV-aided VANETs. In a game, the UAV chooses whether or not to relay a vehicle message to another roadside unit, and smart jammer chooses its jamming power under a UAV channel model with the path loss, log-normal shadowing, and Rayleigh fading. The UAV decision depends on the quality of the channel and BER. The utility of the UAV at time slot k is based on the transmit cost and SINR of the signal received by roadside units and the UAV. The jammer utility at time slot k depends on jamming cost and energy consumption of the UAV. The repeated interactions between jammer and UAVs are formulated as a dynamic game. To show how best the strategy of UAV relay depends on the radio channel model and transmission cost, the Nash equilibrium is derived. Authors proposed a relay strategy based on hotbooting policy hill climbing (PHC) to resist jamming in the UAV-based VANET without the knowledge of jamming model and network model. Results obtained after simulation performance show the hotbooting PRC-based relay strategy can significantly minimized BER of vehicles data and therefore increase payoff of the network compared to Q-learning based scheme. The work in [184] differ from [183] by extending the stochastic game with random channel power gains for the vehicle-UAV and vehicle-roadside unit communication links, and take into consideration the impact of the UAV-roadside unit distance and the speed of vehicle on BER of the vehicle message. In [184], authors also evaluate the anti-jamming UAV relay game with the jammer that changes its jamming policy based on UAVs' learning algorithms.

Prospect theory (PT) is applied to investigate smart attacks against UAV transmission where a selfish and subjective attacker under uncertain attack detection accuracy [165]. In the formulated PT-based game, attacker decides whether to jam or spoof or eavesdrop signals, whereas the target UAV chooses the transmit power based on channel model. The UAVs' goal is to improve its transmission against the attacker by increasing SINR of the signal it sends to the ground mobile node. The PT-based utility of targeted UAV which is based on estimated utility theory and the utility of the attacker is formulated. Nash equilibrium of the game that provides players' best-response if their opponents chooses the NE strategy is defined. To derive the optimal power allocation strategy of the UAV, reinforcement learning techniques are applied to defend against smart attackers. To accelerate UAVs' learning speed especial when the number of attack modes and channel state is large, Q-learning power allocation strategy combines deep learning [185] and Q-learning. In this work, authors proposed Q-learning, Win or Learn Faster-Policy Hill Climbing (WoLF-PHC), and deep Q-network (DQN)-based power allocation strategies for the UAV. Numerical simulation results show that the proposed power allocation strategy can accelerate learning rate of UAV system and increase the secrecy data rate. For instance, in comparison to Q-learning based scheme, reinforcement-learning-based scheme increases the UAV system utility by 22% and secrecy data capacity by 16%, if the total power constraints of the UAV and attacker are both equal to 0.4, and the objective weight of target UAV and attacker equals to 0.8 and 1, respectively.

The existing intrusion and detection methods such as those given in [140], [147], are not sufficient to protect UAV-based system from risks. In fact, these methods do not take into account the compatibility of the sensor and actuator measurements with the UAVs' physical process and control mechanism, which are of great importance in the protection scheme. Moreover, most of these proposed methods [140], [147], [183], [184] only considers small number of UAVs, therefore more research is needed to study the possibility of extending these techniques or designing of new schemes for a large number of UAVs.

The problem of security in wireless communications with UAVs is discussed in this subsection. In detail, the proposed system models and game design approaches are reviewed. Zero-sum pursuit-evasion differential game, Bayesian game, anti-jamming game, and prospect static game are presented as mechanism to address the security problem in UAV-assisted networks. The zero-sum pursuit evasion game was proposed to compute optimal strategy by the team of UAVs evading attack from an aerial jammer in UAV-assisted relay network. Bayesian game is proposed as a framework for new intrusion detection and ejection against lethal attacks in a UAV-aided vehicular network with resource constrains of different nodes in consideration. Two anti-jamming UAV relays game were proposed to resist smart jamming for UAV without knowledge of network and jamming model in a UAV-aided VANET. The prospect theory based smart attack game strategy for UAVs is proposed to address the smart attacks in UAV-aided VANET without the knowledge of the attack model and channel model of the communication system. The discussed games are useful in a scenario where there partial or no information about the attack and channel models.

G. Load Balancing

One of the critical issues in wireless communications is resource management. To meet the ever-increasing demand for wireless bandwidth requires a proper utilization of the available resources. A better distribution of the scarce radio recourses can improve network performance and quality of service. Therefore, an efficient way to load distribution among access points is necessary.

Authors in [142] propose a game-theoretic framework for load balancing between LTE-U unmanned aerial base station (UABS) and WiFi access points (APs), based on the qualities of a users' link and also loads at the ground APs and UABSs. The hybrid cellular network is designed consisting of UABSs equipped with LTE-U capability and WiFi APs to provide coverage to mobiles. Authors proposed a regret-based learning dynamic duty cycle selection method for configuring transmission gaps in LTE-U UABSs, to guarantee a satisfactory network throughput for users. The non-cooperative, *U*-player normal form game proposed comprises of UABSs as players, and is defined as $G = (U, \{S_i\}_{i \in u}, \{\Phi_i\}_{i \in u})$, where S_i is the strategy set and Φ_i is the utility of player *i*. The set of strategy of each player $i \in u$ is composed of its transmission duty cycles. The utility function $\phi_i^t(s_i^t, s_{-i}^t)$ is given as the average cell throughput of the i^{th} UABs for a single duty cycle as,

$$\phi_i^t(s_i^t, s_{-i}^t) = \frac{1}{\|C\|} \sum_{C=1}^{\|C\|} \sum_{K=1}^{N} {}_i^c N_c(k) \omega \log_2(1 + \eta_i^c(X_k))$$

where $s_i^t \in S_i^t$ is the selected strategy by player *i* during t^{th} cycle period, ${}_i^c$ is an ON or OFF state indicator function (i.e., ${}_i^c = 1$ means UABS*i* is in ON state on c^{th} downlink-subframe (DL-SF)), $N_c(k)$ is the number of allocated resource blocks for user *k* on DL-SF, *c* and *w* are the bandwidth of on allocated resource block, and $\eta_i^c(x_k)$ is the SINR value of user *k* from UABs *i* at a location x_k on the DL-SF *c*. To reach correlated equilibrium, the distributed no-regret learning algorithm for selection of UABS $i \in u$ is designed. The simulation results indicate that the aggregate capacity is enhanced compared to fixed duty cycle approach up to 32%.

The approach in [142] maximizes the capacity of LTE-U UABS and minimize interference. However, UABS are assumed to be positioned in order to maximize the coverage, there is no detailed information on how the optimal placement is achieved. The method that combines both, the placement for optimal coverage and load distribution can allow the UABS to autonomously provide maximum coverage with high-quality connectivity. The investigation could also be extended to address the interference and load distribution for *n*-UABS architecture.

In this subsection, the proposed regret based learning dynamic duty cycle selection strategy to configure periodic transmission gaps of LTE-U unmanned aerial base stations co-existing with WiFi network is studied. The hybrid system design and game formulation is discussed. The analysis has shown that using the regret based learning strategy, the heterogeneous WiFi network and unmanned aerial base station can co-exist with improved total network capacity without affecting much the performance of individual radio access.

H. Channel Assignment

Anti-coordination game for radio channel assignment for UAVs and user terminals is proposed in [149]. A combination of UAVs and D2D is considered in forming a network. In this network, inter-UAV and UAV-device links are considered to be primary communication links while D2D links are secondary. Both UAVs and devices are referred to as nodes, which are the players in the game. To maximize channel resource optimization, authors assign partial overlapping channels to the nodes. The problem is formulated as Anti-coordination channel assignment game *G* = (*S*, *M*), with a finite set of players $A = \{a_1, a_2, \ldots a_N\}$ and strategy space $S = Si$. The utility of a player *i*, M_i is considered to be proportional to the connectivity of each player. The total utility of the network referred to as social welfare defined in anti-coordination game is represented as

$$U_{NET}(\Psi) = U_i(\Psi) = \sum_{i \in A} M_i, \forall i$$

Ψ is the cartesian product of the strategy vector of a player defined as the game profile of network. The utility function is defined as a potential function of the game. Therefore the problem is a potential game in which Nash equilibrium existence can be proved and have at least one pure strategy Nash equilibrium. Four learning schemes can be used for the game, namely, better response, best response, foresight response, and smoothed better response. Authors used best response technique to design the Anti-coordination game based partially overlapping channels assignment (AC-POCA) algorithm which allows rapid convergence.

Simulation results obtained after configuring the scenario using C++ indicate the proposed AC-POCA algorithms in mixed network topology outperforms other conventional approaches in terms of the number of active links, hence better aggregate throughput. Moreover, the algorithm has demonstrated fast convergence speed and significantly low signaling overhead. In addition, because the proposed game can minimize interference, the possibility for applying it for optimizing energy becomes worth to explore.

The problem of radio channel assignment in a UAV D2D-enabled wireless network based on anti-coordination game strategy is addressed in this subsection. The interference problem resulting from using arbitrary channels, limited availability of the number of orthogonal channels, high mobility, and dynamic topology of the of UAVs and user devices, make the game theory a more appropriate approach for addressing the channel assignment problem in the network. The proposed algorithms demonstrated to be effective in terms of low signaling overhead and throughput in a dynamic environment.

I. Offloading

Mobile devices and many IoT devices are limited in terms of their battery lifetime, storage, and processing power. To address these challenges, the resource intensive tasks are offloaded to the external powerful platform such as cloud computing for processing and storage [186]. In a cellular network, data offloading frees users' bandwidth by minimizing the amount of data that is carried on the cellular band. Fig. 17 shows different network technologies used for data offloading. Access nodes can be endowed with computing capabilities to offer computation and offloading opportunities to users with limited power and processing capability [187]. Weaker nodes can offload data to a nearby cloud-enabled radio access nodes, UAV-cloudlets, or powerful base stations. Offloading is enabled by uplink and downlink communications between the user's devices and the access nodes or cloudlets.

To optimize computation offloading, a technique using game theory concepts is proposed in [153]. A scenario where UAVs,

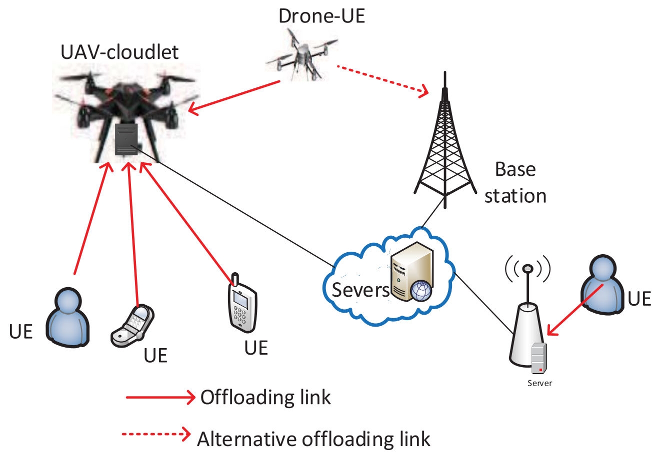

Fig. 17. Network technologies for computation offloading of traffic.

which are used for surveillance, due to their computation capability limitations need to offload their intensive tasks to an edge or cloud server. Authors presented game for choosing computing offloading service for specific tasks while minimizing energy consumption and execution time. The game is modeled as potential game $\mu(N, A, G)$, in which N represents the number UAVs (i.e., players), A are the player's strategies, and G is the global cost function. The strategies are the different choices that a player has, including performing task locally, offloading to a neighboring base station or node through WiFi, and offloading to the cloud server through cellular network. The cost function, in terms of energy consumption execution time for each possible choice, is formulated. The global cost function is designed as a joint equation of energy and time delay, and is represented as follows.

$$Cost = \alpha * T + \beta * E$$

where α and β are the weights of delay time and energy, respectively. The existence of Nash equilibrium is established, and strategic offloading algorithm developed. The experiment results proved that the developed approached outperforms the three offloading models in terms of average system cost when used independently.

The work presented in this subsection considered the problem of offloading intensive computation tasks to decrease execution delay and improve the energy overhead UAV-based edge computing network. To address the problem, game theoretical approach is proposed where the UAVs are given possible choices to carry out computation. The game strategies and cost function are explained. The distributed algorithm performances tested outperform other approaches in terms energy and processing delay.

J. Summary and Conclusion of the Section

The above areas of applications where various game-theoretic were applied are summarized in Table IV. The problem solved, the type of game applied, UAV-assisted network, players, players' strategies, utility function, and solutions are provided.

Because of their potentials and unique characteristics such as quick and easy deployment, ability to provide LoS connection, and fast speed, it is expected that in the future massive UAVs will be deployed for different applications including wireless communications. However, it can be observed that many of the game theory applied to solve problems in UAV-based networks assumes a small number of UAVs in the networks [140], [147], [150], [160]–[162], [183], [184]. With the ever-growing UAV communication systems, there is a need for developing mechanisms that are based on evolutionary algorithms [70]. The conventional game models are not adequate to model large-scale UAV communications systems due to the following reasons. To start, the conventional games demonstrated slow convergence to equilibrium because of the immense signaling and communication overhead caused by information exchange among different UAVs (players) in the network. Another setback of the conventional game theory is the complexity in analyzing the utility function of large-scale multi-agent networks due to complex algorithms resulted from players' collection of information from all other players. Moreover, the conventional games take longer to reach equilibrium for as the number of UAV increases, the size of the payoff matrix increases. Therefore the time required for the game to reach equilibrium also increases. Thus, it becomes necessary to rethink of the different analytical models of tackling the problem in future massive, dynamic and complex UAV wireless networks and move toward models that fit the characteristics of the network more appropriately. Examples of non-conventional games include evolutionary, mean field and minority games. These games allow system scalability, a feature that makes them appropriate for finding the solutions for the problems in massive UAV-aided wireless communications networks.

Despite the wide range of applications of game theory in addressing challenges in UAV-based networks, there are still numerous problems have not been addressed. For instance, quality of experience, trajectory optimization, interference mitigation, transmission control protocols, low latency, and low data rates are among the open research problems.

V. Future Research Directions

To be able to support massive wireless traffic demands, future networks will need to be very dense and multi-layered. Therefore, among other things, a large number of UAVs will be deployed to meet such demands. Complex and dynamic UAV-based networks are expected to present a significant part of the future dynamic and sophisticated communication systems. Swarms of UAVs equipped with wireless communication capabilities will be deployed to assist overloaded networks, replace damaged communication infrastructures, provide network backhaul, relay data, and as various types of flying base stations. In fact, UAVs will be key to realize the future network visions such as the 5G and IoT networks.

Because of the large size, complexity, and dynamic nature of UAV-based networks, they need to have self-organizing capability. Self-organizing wireless networks can tremendously

TABLE IV
SUMMARY OF THE CHALLENGES WHERE GAME THEORETIC CONCEPT IS USED TO FIND SOLUTIONS

Issue	Game type	UAV-assisted network (Player)	Strategy/objective	Utility	Solution	Ref.
Optimal height and coverage	Non-cooperative games	Aerial base stations (UAVs)	Find best possible next location by changing position (horizontal and vertical) seeking to cover more nodes	Maximum coverage over the area it provide coverage	Non cooperative game algorithms and simulations	[161], [162]
Coordination and mobility control	Non-cooperative game	Aerial base stations (UAVs)	Choose the best moving strategy to maximize mobile coverage	Maximum mobile coverage	Non cooperative game algorithms and simulations	[144]
			Drone base stations move with constant speed and fixed height while choosing best turning angle and direction to optimize performance	Best direction that yield optimal performance	Distributed mobility control algorithms	[163]
	Evolutionary game	Aerial base station (UAVs)	Choose the best moving strategy to maximize mobile coverage	Maximum mobile coverage	Evolutionary algorithms (EA) for evolving flying maneuverer in a collaborative manner	[144]
	Population game	Not specified (UAVs)	UAV follows already established trajectories by following the leader UAV in performing formation	Best formation for maximum coverage	Distributed control formation algorithms	[145]
Performance efficiency	Hedonic coalition formation game	Relay, Ad-hoc network (UAVs and Tasks)	Form a coalition that will yield the best result in terms of time and energy	Minimum delay and energy consumption	Distributed algorithms for coalition formation	[69]
Energy saving and power optimization	Sub-modular game	Aerial base stations (UAVs)	Periodically sending a beacon searching for mobiles	Minimum energy consumption	Distributed algorithms for best beaconing duration	[150]
	Non-cooperative game	Aerial base stations (UAVs)	Move to the right position	Maximum mobile coverage	Non cooperative game algorithms	[161], [162]
	Nash bargaining game	Aerial base stations (UAVs)	Periodically sending a prob alerting ground users	Maximum mobile coverage	Nash bargaining solution algorithms	[152]
Network security	Zero-sum pursuit evasion game	Not specified (UAVs)	Avoid an attacker who wants to jam a communication channel	Minimize the jammer's termination time	Optimal control algorithms	[140]
	Reinforcement learning	VANET (UAVs and vehicles)	Choose whether or not to relay to another roadside unit depending on the quality of the channel and the BER	minimized the bit-error-rate (BER)	hotbooting policy hill climbing (PHC)algorithm	[183], [184]
	Prospect game	VANET (UAVs)	Chooses the the transmit power based on the channel model	Improve UAV transmission by increasing SINR of the signal it sends to mobile node	Win or Learn Faster-Policy Hill Climbing (WoLF-PHC) and deep Q-network (DQN) algorithms	[165]
	Bayesian game	VANET, MANET (UAVs)	Identify and eject an intruder	Minimized delay and achieve a better delivery ratio	Formulated Bayesian Nash equilibrium	[147]
Capacity maximization	Zero-sum pursuit evasion game	Relay (UAVs)	Avoid an attacker who wants to jam a communication channel	Maximize the capacity by being as far as possible for the jammer	Optimal control algorithms	[141], [160]
Load balancing	U-player normal form game	Aerial base station (UAVs)	Selection dynamic duty cycle that maximizes throughput	Satisfactory average throughput	Distributed no-regret learning algorithm	[142]
Channel assignment	Anti-coordination game	D2D, Relay (UAVs)	Choosing best channel for minimum resource utilization	Social welfare	Anti-Coordination game based Partially Overlapping Channels Assignment (AC-POCA) algorithm	[149]
Offloading	Potential game	Mobile edge network (UAVs)	Choosing computing offloading service for specific tasks while minimizing energy overhead and time for execution.	Minimum energy consumption and delay	The strategic offloading algorithm	[153]

enhance network capacity, improve quality of service, and reduce operational costs by removing human involvement in performing operations. However, addressing interference challenge in such UAV-assisted networks require advanced techniques that fit the nature and characteristics of the networks.

A. Interference in Massive UAV-Based Networks

Severe interference has been one of the major challenges in designing and deployment of massive UAV for communication systems. Because self-organizing networks of UAV-based networks use the sharing wireless channel for transmitting information, they are facing complex wireless signal interference [65]. In addition, the exponential increase in demands of spectral efficiency, data rate, degrees of freedom, and network capacity due to the massive growth of end devices, it is expected that in the future large number of UAVs will be deployed to assist and expand the network. Deployment of a large number of UAVs will intensify the interference problem, which can severely affect the transmission capacity and performance of the network. In UAV-based networks, there are several sources of interference, including cross-layer interference, co-layer interference and inter-UAV interference. Cross-layers interference is the mutual interference between macro cells (UAVs/terrestrial macro cells) and UAV-based small cells. Co-tier interference is the interference among UAV-based small cells where the coverage of one small cell overlap with another. Reducing interference can minimize conflict and retransmission of signals, thus reducing the waste of energy; improve the network throughput and long life.

The dynamic and complexity nature of UAV-assisted network demands new techniques to address the problem of interference management. In addition, because of large number of cells and devices that are expected to be deployed in the future networks, there is a needed for distributed strategic learning schemes that will allow the networks to have self-organization capability, less exchange of information, and high degree of autonomy. Distributed schemes do not require a central entity and reduce the control and computational overhead due to limited channel state information and feedback. Therefore, in the following subsection we propose advanced distributed methods for addressing interference challenges in UAV-based wireless communication networks.

B. Advanced Distributed Schemes for Interference Management

Because of the large size, complexity, and dynamic nature as well as the need for self-organization, using centralized techniques in managing interference is difficult. Centralized approaches cause backhaul network congestion and this will limit the amount of information that can be exchanged with the operator. Therefore, advanced distributed schemes needs to be employed to address the interference challenge in UAV-based networks. In UAV-based networks, distributed interference management scheme will include different types of players such as UAVs, BSs, and UEs. The schemes will also involve multi-dimensional strategy spaces including power, 3D locations, and hover or flight times. In addition, the distributed schemes allow networks to have self-organizing capability, allowing the operation of interference management to be performed autonomously by devices themselves. The techniques also reduce the control and computational overhead, due to limited channel state information and feedback. Mean field game (MFG) and Reinforcement learning (RL) are the proposed distributed techniques for formulating interference management problem.

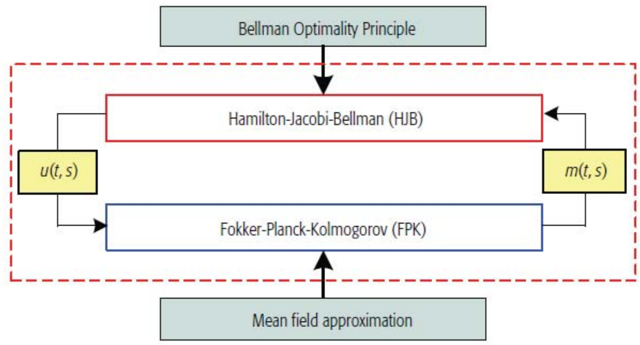

Fig. 18. The basics of mean field game [188].

1) Mean Field Game: As an advanced game, mean field game (MFG) can be used for analyzing the dynamics of a large number of interacting rational agents in which there is a heavy exchange of information. Therefore MFG is the right scheme for modeling, formulation, and solving interference management problems in large, complex, and dynamic UAV-based networks [189]. While traditional game theory models the interaction of individual player with every other players in the network, MFG can model the interaction of individual player with the effect of mass (collective) behavior of the players [70]. The collective behavior of players is reflected in the mean field, whereby each player selects its strategy according to its own interests, state, and the state of the mass of players (i.e., mean-field value) who simultaneously select theirs in a similar way. The aim of each player in MFG is to find a strategy that gives maximum utility over a predefined period of time by considering the collective behavior of other players.

With MFGs, the interference problem for ultra-dense UAV-based communication systems can be modeled by describing the behavior of the system using only two differential equations, the Hamilton-Jacobi-Bellman (HJB) and the Fokker-Planck-Kolmogorov (FPK) equations. The interaction of an individual player with the mean field is modeled by the HJB equation. The mass dynamics according to the action of the players are described by the FPK equation. The HJB and FPK equations are also known as forward and backward equations, respectively [190]. The HJB and FPK partial differential equations interact with each other as shown in Fig. 18. The value function u and mean field value m, are solutions of HJB and FPK equations, respectively. The MFG solution, given by a pair of maps (u, m), is obtained by solving the FPK and HJB equations.

As a special form of differential games, MFGs allow the stochastic nature of system such as channel dynamics to be taken into consideration. In addition, MFG models allow the derivation of offline algorithms which do not depend on any exchange of information among entities while executing the algorithm. This is possible because the entities are required to collect the needed information only at the initialization stage before algorithm execution. This element

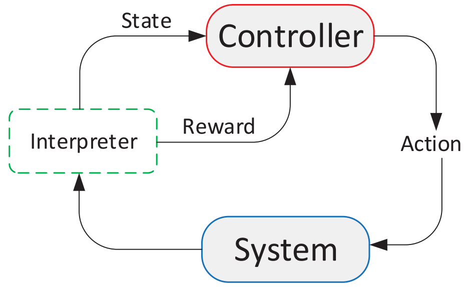

Fig. 19. The basic reinforcement learning scenario.

makes MFGs significantly attractive because it needs limited backhaul/fronthaul connectivity.

2) Reinforcement Learning Algorithms: Reinforcement learning (RL) is a branch of machine learning which enables systems to automatically learn from their past experience and environment, and use the feedback to improve their performance [191], [192]. The main components of an RL framework are rewards, states, and actions. In RL, players maximize their individual utility by choosing or avoiding certain actions based on the feedback obtained from past measurements. Choices that previously led to high reward in a particular situation tend to be repeated whenever similar situation occurs again, whereas actions that yielded comparatively lower reward are avoided. Fig. 19 shows a typical framing of RL scenario, where a controller take action in a system environment, which is interpreted into a system's state and reward, which are then sent back to the controller. Basically, RL techniques allow players to learn their optimal policy gradually by exploring and exploiting the environment, simultaneously [192].

RL based algorithm is a typical example of a fully distributed algorithm that can be used to minimize communication overheads in the network [193]. This is because the algorithm does not require players to know anything about other players. Each user learns about the game by observing only its own achieved payoffs. Over time, using only this information, a player can rationally choose the best course of actions to maximize its utility.

RL can be leveraged to model and optimize UAV-assisted wireless communication networks. For instance, using RL based algorithms, UAVs can dynamically adjust their motion control, flight directions, and positions to serve better their users on the ground. Using RL algorithms, UAVs can rapidly self-organize themselves to adapt to the dynamic environments, and autonomously optimize their positions and trajectory, thus, minimize energy consumption and interferences.

As an indication of its usefulness in solving different challenges in UAV-based wireless communications, recently, researchers have started utilizing RL techniques [194]–[197]. In [194], an optimal trajectory of an UAV acting as a BS is designed by leveraging the tools of RL. Authors applied Q-learning, which is a model-free RL technique to train an autonomous UAV to make movement decisions that maximizes sum of transmission rate during flying time. Authors in [195] proposed an interference-aware path planning scheme for UAVs supported by a cellular network using dynamic game. The game is solved using deep RL algorithm, and the results obtained show reduction in wireless latency and interference that UAVs cause to the terrestrial network along their path. UAV-aided 5G communication scheme against jamming using deep RL method is designed in [196]. In this framework, UAV chooses optimal relay policy to assist 5G system against smart jamming and the simulations show that the method can obtain optimal anti-jamming communication performance.

C. The Benefits and Feasibility of UAVs in 5G networks

Due to the promising development of IoT and mobile Internet, there exist unique communication requirements of ultra-reliable low latency communications (uRLLC), massive machine-type communication (eMTC), and enhanced mobile broadband (eMBB). Meanwhile, UAVs are also expected to be used to assist VANETs and WNSs. It is necessary to study the characteristics and advantages of deploying UAVs to assist these networks. Moreover, the feasibility studies on the use of UAVs to augment the wireless networks are needed to accelerate its development and deployment.

VI. CONCLUSION

This paper has provided a summary of the recent developments in game theory for UAV-aided wireless communications. Game theory is a powerful tool that can be used to examine complicated interactions and make decisions. The potential of applying game theory to wireless communication with UAVs is prospective. In this survey we have mentioned the current and future applications of UAVs for different functions including wireless communications. We have provided the benefits and challenges of using UAVs for wireless communication networks. We described UAV-based wireless networks and discuss UAVs' applications in the existing networks and their potential in achieving future IoT and the 5G visions.

We have provided an overview of game theory by giving a brief introduction and definitions of relevant terms used in game theory. We have outlined the existing game theoretical approaches used to solve various challenges in UAV-aided networks and their classification to provide interested readers with a comprehensive understanding of game theory for wireless communication with UAVs. We surveyed an up-to-date, state-of-the-art literatures reviews of game theory utilized to find solutions to various UAV-based communications challenges. We identified open research issues that need further investigation, and proposed distributed frameworks for addressing challenges, in particular, interference management in the future massive UAV-based networks.

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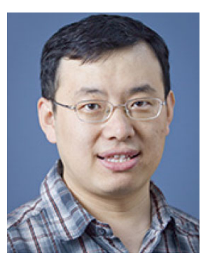

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