Game Theoretic Approaches for Multiple Access in Wireless Networks: A Survey

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Game Theoretic Approaches for Multiple Access in Wireless Networks: A Survey

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Abstract

Multiple access methods in a wireless network allow multiple nodes to share a set of available channels for data transmission. The nodes can either compete or cooperate with each other to access the channel(s) so that either an individual or a group objective can be achieved. Game theory, which is a mathematical tool developed to understand the interaction among rational entities, can be applied to model and to analyze individual or group behaviour of nodes for multiple access in wireless networks. Game theory also enables us to model the selfish/malicious behaviour of nodes, and subsequently design the punishment or defense mechanisms for robust multiple access in wireless networks. In addition, game models can provide distributed solutions to the multiple access problems, which are based on solid theoretical foundations. In this survey, we provide a comprehensive survey on the game models (e.g., noncooperative/cooperative, static/dynamic, and complete/incomplete information) developed for different multiple access schemes (i.e., contention-free and contention-based random channel access) in wireless networks. We consider time-division multiple access (TDMA), frequency-division multiple access (FDMA), and code-division multiple access (CDMA), ALOHA, and carrier sense multiple access (CSMA)-based wireless networks. In addition, game models for multiple access in dynamic spectrum access-based cognitive radio networks are reviewed. The major findings from the game models used for these different access schemes are highlighted. To this end, several of the key open research directions are outlined.

Index Terms: Wireless networks, game theory, multiple access, random access game, power and rate control game.

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I. Introduction

Game theory is a branch of applied mathematics which is concerned with how rational entities make decisions in a situation of conflict. It provides a rich set of mathematical tools to model and analyze interactions among the rational entities, and the rationality of these entities is based on gains or payoff perceived by these entities. Game theory has been primarily used in Economics. It has also been used in other disciplines such as Biology, Political science, Engineering, and Philosophy. One of the major areas in Engineering where game theory has been used is communication networking. In particular, it has has been used to model and analyze routing and resource allocation problems in a competitive environment, and more recently to security problems in wireless networks. Applicability of game theory tools to analyze power control, waveform adaptation, medium access, routing, and node participation was discussed in [1] from a layered perspective.

In a multi-user wireless communication network, the transmitting nodes share the limited radio resources (e.g., wireless channels and transmission power). Therefore, one critical issue is how the nodes share these resources to transmit data so that the optimal network performance can be achieved. Multiple access methods developed for wireless networks can be divided into two main groups, namely, contention-free channel access and contention-based random access methods. In a multiple access scheme, nodes can either cooperate or compete to achieve their objectives (e.g., optimal throughput and quality-of-service (QoS)). Consequently, game theory has become a very useful mathematical tool to model and analyze multiple access schemes in wireless networks, and to obtain solutions for resource allocation, channel allocation, power control, and cooperation enforcement among the nodes. The notion of *multiple access game* can be illustrated by the following example [2], [3]. Suppose that there are two mobile nodes tx_1 and tx_2 who want to access a shared wireless channel to send information to the corresponding receivers $rcvr_1$ and $rcvr_2$. Both the receivers are within the transmission range of both the transmitters. Each transmitter has one packet to transmit in each time step and it can either choose to transmit during a time step or wait. If tx_1 transmits, the packet is successfully transmitted if tx_2 chooses not to transmit during that time step (and hence there is no collision). For successful packet transmission tx_1 obtains a benefit at the cost of transmit power. It is of interest to analyze the interactions between the transmitters under different network settings and performance objectives.

Different game models (e.g., noncooperative/cooperative, static/dynamic, and complete/incomplete information games) have been developed to study the behavior of transmitting nodes to access the wireless channel(s) and obtain the multiple access solution (or equilibrium) [2], [4]. Various game models are considered under different scenarios, perspectives, or assumptions on transmitting nodes' behavior. Nevertheless, the common aim of these models is to improve network performance (e.g., throughput maximization, resource consumption minimization, and QoS guarantee) given self-interest or group-rationality of transmitting nodes.

The motivations of using of game models for design, analysis, and optimization of multiple access in wireless networks are as follows:

- *Theoretical foundation for multiple access schemes*: Game theory, which is most notably used in Economics, usually considers a multiplayer decision problem. A success or benefit of an individual in making decisions depends on the decisions of others. Game theory provides a theoretical basis to analyze interactions in multiplayer systems including human as well as non-human players (e.g., computers, animals, and plants) [5]. Therefore, it can be applied to a wireless communication network in the context of resource sharing where the players are the nodes (e.g., mobile stations, base stations, access points) in the network. Cooperation or competition among mobile nodes for channel access in a wireless network is a multiplayer decision problem, which can be modeled as a game. The benefit of a node as a result of its chosen action (i.e., strategy or move) can be measured in terms of performance metrics such as throughput and delay. An equilibrium solution of the game model defines the actions of the different nodes (e.g., transmission power) for which the chosen performance objective is optimized.
- *Modeling selfish/malicious behavior of nodes*: The transmitting nodes in a wireless network may behave selfishly in order to reap performance advantage over other nodes, as a result of which the overall network performance may degrade. To make the network robust against the selfish behaviors (or attacks) by these malicious nodes, efficient defense mechanisms need to be built into the system. Game theory can be used to model and analyze the selfish behavior of nodes and design the defense mechanisms for robust multiple access in wireless networks.
- *Distributed protocols*: In many scenarios wireless nodes make their decisions in an individual (or distributed) manner rather than in a centralized manner. Game theory is a suitable tool to optimize wireless access distributively [6]. In a centralized scheme, solving the problem of multiple access may become computationally expensive when the network size increases. Also, the network control overhead could be prohibitive. In contrast, efficient distributed algorithms can be designed based on game theory which can reduce the communication and computation overhead significantly. Therefore, game theory is a useful tool to develop efficient distributed protocols for wireless networks. With an appropriate game formulation, cross-layer optimization can be also performed in a distributed way.
- *Mechanism design*: The parameters of a game can be designed (or varied) such that it leads to the independent and self-interested wireless nodes toward a system-wide desirable outcome. Pricing is one technique that can be used for such mechanism design (or incentive scheme) to regulate the usage of radio resources by the wireless nodes by adjusting their costs.

This article comprehensively surveys the existing researches on game theoretic approaches for channel access in a multiuser wireless network. The aim of this article is to familiarize the readers with the state-of-the-art research on this topic and the different techniques for game theoretic modeling of the multiple access problem in wireless systems. Different types of game models are reviewed for both contention-free and random channel access schemes. For contention-free channel access, time-division multiple access (TDMA), frequency-division multiple access (FDMA), and code-division multiple access (CDMA)-based wireless networks are considered. For contention-based channel access, game models for ALOHA and carrier sense multiple access (CSMA)-based channel access methods are reviewed.

The rest of the paper is structured as follows: Section II presents an overview of multiple access methods for wireless networks. Then, an overview of game theory and its applications to multiple access design is presented in Section III. Next, we review the game models for contention-free channel access and random channel access in Section IV and V, respectively. Section VI provides a summary of the survey and discusses several open research issues. Section VII concludes the paper.

II. Overview of Multiple Access Methods

In this section, the general concepts of channel access and performance issues related to multiple access design in wireless networks are discussed.

A. General Concepts

Channel access methods in wireless networks can be divided into two main groups, namely, contention-free channel access and contention-based random channel access schemes. In contention-free schemes, multiple nodes are allocated with the radio resources (e.g., time slot, channel, and code) by a central entity and the nodes use the allocated resources for data transmission [7]. Contention-free channel access can be used in time-division, frequency-division, and code-division multiple access networks.

- *Time-division multiple access (TDMA)*: In TDMA, time is divided into fixed-length frames and each frame is divided into multiple time slots. Time slots are allocated to the nodes for data transmission. In TDMA, synchronization among the nodes is required to avoid interference [8].
- *Frequency-division multiple access (FDMA)*: In FDMA, radio frequency band is divided into multiple channels. The channels are allocated to the nodes for data transmission. Orthogonal frequency-division multiple access (OFDMA) is an improved version of FDMA which is based on the orthogonal frequency-division multiplexing (OFDM) modulation in the physical layer. In OFDMA, frequency band is divided into multiple subcarriers which are shared among the nodes. OFDMA is used in the IEEE 802.16-based WiMAX networks.
- *Code-division multiple access (CDMA)*: In CDMA, multiple nodes can transmit data on the same channel simultaneously. The transmitted data by each node is encoded by using a unique spreading code. The spreading codes for the different

users are orthogonal/near-orthogonal to each other. The receiver of each node can decode the original data correctly if the signal-to-interference-plus-noise ratio (SINR) is maintained above a threshold.

For contention-based random access scheme, a node has to compete with other nodes to transmit data over the wireless channel. A packet transmitted by a node will be received successfully if there is no collision. A collision occurs when multiple nodes transmit data simultaneously and the SINR at the receiver is lower than the minimum SINR required to decode the original packet correctly. If collision occurs, a node may attempt to retransmit the packet, and the specifics of the retransmission method depend on the protocol used. The most common contention-based channel access schemes are as follows [9]:

- *ALOHA*: In ALOHA, if a node has a packet to send, it will attempt to transmit the packet immediately. If the packet collides with packets from other nodes, the node will retransmit the packet later. The ALOHA protocol can be operated in a slotted fashion, in which case, time is divided into slots, and packet transmissions are aligned with the time slots.
- *Carrier sense multiple access (CSMA)*: CSMA is a probabilistic medium access method in which a node senses the status of the channel before attempting transmission. If the channel is idle, the node initiates a transmission attempt. If the transmission is unsuccessful due to a collision, the node waits for a packet retransmission interval and transmits again. Two of the improved variants of CSMA are CSMA with collision detection (CSMA/CD) and CSMA with collision avoidance (CSMA/CA). In CSMA/CD, assuming that a node is able to detect a collision, a transmission is terminated as soon as a collision is detected. The collision can be avoided by expanding the retransmission interval (i.e., backoff period) for the node to wait before a new transmission. In CSMA/CA, if the channel is sensed busy before transmission, to decrease the probability of collisions on the channel, transmission is postponed for a random period of time.

B. Performance Issues in Multiple Access for Wireless Networks

The key requirements for the design and optimization of multiple channel access schemes for wireless networks are as follows [10]:

- *Maximize network throughput*: Throughput refers to the amount of data successfully transmitted by the nodes over a time period. Maximizing the overall system throughput is a key objective of most of the multiple access schemes. This is turn improves the spectrum efficiency in wireless networks.
- *Minimize delay*: Delay refers to the time required for a packet to be transmitted successfully since it has been received at the transmission buffer from the upper layer. Delay is a key performance metric for real-time traffic (e.g., voice and video). Multiple channel access schemes for such traffic have to minimize delay.

- *Guarantee fairness*: Fairness is a measure of whether the nodes are receiving an equal (or fair) share of radio resources. Multiple channel access schemes must guarantee a certain level of fairness to all nodes in the network.
- *Improve power efficiency*: Power efficiency is an important performance metric for battery-powered wireless nodes. There is a tradeoff between power efficiency and network performance. To reduce power consumption, a node can be put in standby mode during which the node cannot transmit and/or receive packets. Consequently, the throughput reduces.

In a wireless network, the nodes sharing the limited radio resources may have different behaviors. On one hand, all nodes can cooperate to meet the above requirements and achieve optimal network performance. This is referred to as *group rationality*. On the other hand, the nodes can be noncooperative to compete with each other for the radio resources. This is referred to as *self-interest* behavior. To analyze these behaviors and investigate their impact on network performance, game theory can be applied through which the equilibrium solution (i.e., behavior of the nodes at steady state) can be obtained.

III. Overview of Game Theory and Its Applications to Multiple Access

In this section, the basic concepts used in game theory are discussed and different game models are introduced. The issues pertinent to using game theory to analyze multiple access schemes in wireless networks are also discussed.

A. General Concepts

A game is defined by a set of players, a set of actions for each player, and the payoffs for the players. A player chooses an action and the complete plan of action is referred to as the strategy. When the action is chosen deterministically, it is called a pure strategy. On the other hand, when the action is chosen probabilistically according to a certain probability distribution, it is called a mixed strategy. Based on the strategies of the players, their payoffs are determined. Depending on the nature of the game, there are different solution concepts. However, almost all of them rely on the equilibrium concept which ensures that a player will gain a fair or optimal payoff given the strategies of the other players in the game. Pareto optimality or Pareto efficiency is another well-known concept in a game. A strategy is called Pareto optimal if it is impossible to make one player better off without necessarily making other players worse off.

B. Game Theoretic Models

Two major game-theoretic approaches which can be used to model multiple access schemes are the noncooperative and the cooperative game approaches. In a noncooperative game, the players make rational decisions considering only their individual payoff. In a cooperative game, players are grouped together and establish an enforceable agreement in their group.

1) Noncooperative games: Self-interested players in a noncooperative game make decisions independently. The players are unable to make enforceable contracts but it does not mean that players do not cooperate. Any cooperation in the games must be self-enforcing. Noncooperative game theory has been used extensively to study various issues in wireless networks (e.g., medium access control game, time slot competition, and power control in CDMA). The goal of a noncooperative game model is to find the equilibrium solution for networks with self-interested nodes. A well-known solution concept for a noncooperative game is *Nash equilibrium* [11]. A Nash equilibrium is a set of strategies for the players such that no player has any intention to change his/her strategy to gain a higher payoff given that none of the other players changes his/her strategy.

Let i be an index of a player, $i \in \mathbb{I} = \{1, \ldots, M\}$ where $\mathbb{I}$ is a set of players and M is the total number of players. Let $\mathbb{S}_i$ denote a set of strategy of player i. $s_i \in \mathbb{S}_i$ is any possible strategy of player i. The Nash equilibrium satisfies the following condition [11]:

$$u_i(s_i^*, \mathbf{s}_{-i}^*) \geq u_i(s_i, \mathbf{s}_{-i}^*), \quad \forall i \in \mathbb{I}, \quad \forall s_i \in \mathbb{S}_i \tag{1}$$

where $u_i(\cdot)$ is the payoff function of player i, s_i^* is a Nash equilibrium strategy of player i, and $\mathbf{s}_{-i}^*$ is a Nash equilibrium strategy vector of all players except player i. However, a Nash equilibrium may not exist in a game. Also, even if a Nash equilibrium exists, it may not be unique.

Another solution concept which is more general than the Nash equilibrium is known as *correlated equilibrium* [12]. In this concept, a strategy profile is chosen according to the joint distribution instead of the marginal distribution of players' strategies as in the Nash equilibrium solution. The definition of correlated equilibrium is given below. Let $\mathbb{S}_i$ denote a set of strategies of player i. A probability distribution π over $\mathbb{S}_1 \times \cdots \times \mathbb{S}_M$ is a correlated equilibrium if for every strategy $s_i^* \in \mathbb{S}_i$ such that $\pi(s_i^*, \mathbf{s}_{-i}) > 0$, and every alternative strategy $s_i \in \mathbb{S}_i$, it holds that,

$$\sum_{\mathbf{s}_{-i} \in S_{-i}} \pi(s_i^*, \mathbf{s}_{-i})[u_i(s_i^*, \mathbf{s}_{-i}) - u_i(s_i, \mathbf{s}_{-i})] \geq 0, \quad \forall i \in \mathbb{I}, \quad \forall s_i \in \mathbb{S}_i. \tag{2}$$

To interpret this definition, given a recommendation (i.e., a recommended strategy according to the distribution π) to player i, a distribution π is defined to be a correlated equilibrium if no player i can choose a strategy s_i instead of s_i^* which results in a higher expected payoff.

A noncooperative game can be classified as either a complete or an incomplete information game. In a complete information game, information such as the payoffs and strategies of the players are observable to all the players. On the other hand, in an incomplete information game, the information is unknown by other players. An incomplete information game can be modeled as a Bayesian game [11] in which Bayesian analysis is used to predict the outcome of the game. The equilibrium solution of such a game is called *Bayesian Nash equilibrium*. Similar to the Nash equilibrium in a complete information game, a Bayesian

Nash equilibrium can be obtained in which each player seeks for a strategy profile that maximizes its expected payoff given its beliefs about the *types* and strategies of other players.

Moreover, a game can be classified either as a static game or a dynamic game. A static game is a one-shot game where all players make decisions without knowledge of the strategies that are being chosen by other players. The one-shot game ends when actions of all players are chosen and payoffs are received. In contrast, in a dynamic game, a player chooses an action in the current stage based on the knowledge of the actions chosen by the other players in the current or previous stages. This dynamic game can be called a sequential game since players play a static game repeatedly. The common equilibrium solution in dynamic games is a subgame perfect Nash equilibrium [13]. A subgame perfect Nash equilibrium represents a Nash equilibrium of every subgame of the original game. A common method to obtain subgame perfect equilibria is backward induction.

A dynamic game with incomplete information can be described as a multi-stage game when information is unknown to other players [11]. It is similar to a dynamic game with complete information in that the players take turns sequentially rather than simultaneously but information is incompletely known to others. The players follow their beliefs and dynamically update their beliefs by using the Bayes' rule. In a dynamic game with incomplete information, perfect Bayesian equilibrium is the solution concept which can be considered as a combination of the Bayesian Nash equilibrium and subgame perfect equilibrium concepts.

Repeated game [11] is a special kind of dynamic game in which the same set of players play the same stage game or one-shot game repeatedly over a long time period. Repeated games can be divided into two key types, namely, finite and infinite repeated games, depending on whether the period of time during which the game is played is finite or infinite. Most repeated games are typically infinite repeated games and a player takes into account the effect of his or her current action on the future actions of other players.

Markovian game (i.e., Markovian dynamic game or Markov game) is an extension of game theory to Markov Decision Process-like environments. A Markovian game can be defined as a type of stochastic game [14]-[15] which can be regarded as a multiagent extension of Markov decision process [16]. The key difference between a Markov game and a Markov decision process is that a transition depends on the current state and the action profile of the players and each player may receive different reward as a result of the action profile. Each player has a reward function (i.e., payoff function) and tries to maximize its expected sum of discounted reward. A more specific type of Markovian game is a *switching controlled Markovian game* where the transition probability in any given state depends on the action of only one player. The Nash equilibrium for such a game can be computed by solving a sequence of Markov decision processes.

Auction game [17] is a game theoretic approach in which an object or service is exchanged on the basis of bids submitted by the bidders to an auctioneer. There are two main auction mechanisms, namely, the first and second price auctions. In first price auction, an object or service is given to a bidder who submitted the highest bid and pays a price equal to the amount of bid. In second price auction, an object or service is given to a bidder who submitted the highest bid and pays a price equal to the second highest amount bid.

Stackelberg game or leader-follower game [11] is a strategic game in which the player acting as a leader moves first and then the rest acting as followers move afterward. Then, the problem is to find an optimal strategy for the leader, assuming that the followers react in such a rational way that they optimize their objective functions given the leader's actions. The Stackelberg game model can be solved by subgame perfect Nash equilibrium.

Evolutionarily stable strategy (ESS) [18] is a solution concept in the evolutionary game theory. In this game, the evolution of social behaviour of animals in a population is considered. In a wireless network, a population can be a group of mobile nodes sharing the channels. A strategy is called an ESS if in a fixed population, the entire population using ESS cannot be invaded by mutant strategies of a small group.

2) Cooperative games: In a cooperative game, players are able to make enforceable contracts. The players in a coalition cooperate to maximize a common objective of a coalition. In this case, players can coordinate strategies and agree on how the total payoff is to be divided among players in a coalition. Nash bargaining game is one type of cooperative games where the players maximize the product of their gains given what each player would receive without cooperation (i.e., threat point). This is referred to as the Nash bargaining solution which can be defined as follows:

$$\mathbf{s}^* = \arg\max_{\mathbf{s}} \prod_{i \in \mathbb{I}} (u_i(s_i) - u_i^{\mathrm{d}}) \tag{3}$$

where $u_i(\cdot)$ is the payoff function of player i, s_i is a strategy of player i, and $\mathbf{s}^*$ is a Nash bargaining solution strategy vector of all players, and u_i^{d} is the threat point (i.e., the utility gained if player i decides not to cooperate and bargain with the other players).

Coalition formation game is a cooperative game involving a set of players who are looking for cooperative groups (i.e., coalitions). A coalition $\mathbf{S}$, which represents an agreement among the players to act as a single entity, can be formed by players in a set $\mathbf{N}$ to gain a higher payoff, and the worth of this coalition, denoted by v is called the *coalitional value*. Two common forms of coalitional games are *strategic form* and *partition form*. In the former case, the value of a coalition $\mathbf{S}$ depends on only the members of that coalition (i.e., independent of how the players in $\mathbf{N}\backslash\mathbf{S}$ are structured). In the latter case, the value of a coalition $\mathbf{S}$ strongly depends on how the players in $\mathbf{N}\backslash\mathbf{S}$ are structured. Again, coalitional game models can be developed with either transferable payoff or non-transferable payoff. In a transferable payoff coalitional game, there is no restriction on

TABLE I

SUMMARY OF GAME MODELS

Game model	Key objective	Solution concept	Type
Noncooperative game	Individual players act to maximize their own payoff.	Nash equilibrium, Correlated equilibrium, Bayesian Nash equilibrium, Evolutionary stable strategy, Stackelberg equilibrium.	Static game vs. dynamic game (e.g., repeated game), Complete information game vs. incomplete information game, Evolutionary game, Markovian game, Stackelberg game, Auction game.
Cooperative game	Coalitions of players are formed and players have joint actions to gain mutual benefits.	Nash bargaining solution	Coalitional game Bargaining game

how the total payoff will be divided among the members of a coalition. In a non-transferable payoff coalitional game, the payoff that each player in a coalition obtains depends on the joint actions that the players of a coalition select [19]. A stability solution for a coalition formation game ensures that the outcome is immune to deviations by groups of players (i.e., no player has an incentive to move from its current coalition to another coalition).

C. Issues in Game Theoretic Design of Multiple Access Schemes

Game theory can be used to model and analyze cooperative and noncooperative behaviors of nodes and their interactions during channel access in wireless networks. There are a few considerations when game theory is applied to model and analyze multiple access schemes in wireless networks.

- *Self-interest and group-rationality*: Most of the game theoretic models developed for multiple access in wireless networks have the assumption of self-interest and group-rationality for the noncooperative and cooperative game models, respectively. A node with self-interest has the objective to maximize only its own payoff. However, this behavior may not provide a socially optimal solution. The corresponding depreciation is called price of anarchy. On the other hand, group-rational nodes can cooperate to achieve a socially optimal solution, and for this, a cooperative game (e.g., bargaining game) can be applied [20]-[21]. However, in many cases, the group-rationality condition may not hold for all nodes, and some nodes may deviate from cooperation. Therefore, a penalization (or punishment) mechanism is required to enforce cooperation among the nodes so that a socially optimal solution can always be achieved.
- *Penalization mechanisms*: These mechanisms [22] are proposed to promote cooperation in multiple access among nodes sharing the channel. The punishment is commonly applied to the nodes deviating from cooperation since such deviation

can degrade the network performance. In this respect, two important issues are the detection of deviating nodes and designing the punishment mechanism to be applied.

- *Practical implementation*: Although game theory provides solutions for a situation of conflict during multiple access, it is still difficult to implement these solutions in a practical environment. In many cases, distributed implementations are desirable. In some distributed implementations, the mobile stations may require information such as SINR, power, price from the base station(s) in order to converge to the equilibrium solution. However, in a realistic scenario, these information cannot be observed perfectly (e.g., channel gain of other nodes). Therefore, the mobile stations may need to have the ability to learn from the radio environment which may increase the complexity of implementation and reduce the rate of convergence of the solution of the game to the equilibrium solution.
- *Payoff function*: A payoff function represents the benefit or reward to a player in the game when an action is chosen by this player. Defining a suitable payoff function is an important issue. When the payoff function is defined differently, the solution of the same game model applied to the same multiple access scheme can be dramatically different. The payoff function should be defined considering the physical performance measures of the nodes and/or networks.

In the following sections, we review various game theoretic models proposed in the literature to study multiple access schemes. This review is categorized based on different types of multiple access methods and types of the game models used.

IV. Game Models for Contention-Free Channel Access

In this section, game models for contention-free channel access based on TDMA, FDMA, and CDMA are reviewed.

A. *TDMA-Based Channel Access Games*

Since the nodes have to transmit data during their allocated time slots, in TDMA-based channel access games, the nodes compete for time slots to achieve their performance objectives (i.e., QoS requirements). Four different game models, namely, *noncooperative static game*, *auction game*, *dynamic game*, and *repeated game* models are discussed. A summary of the key features of these game models is provided in Table II. The details of these models are discussed next.

1) Noncooperative static game-theoretic approach: In [23], a noncooperative static game model for QoS-aware resource competition is proposed for a single-hop wireless network with multiple wireless links. The wireless nodes need to compete for the transmission time within a time slot. The power consumption of all nodes is assumed to be constant and the channel fading is assumed to follow a stationary flat-fading process. Two nodes are considered as the players in the game. The time slot length is denoted as $t_i T$ where $t_i \in [0, 1]$ is the time slot share of node i (i.e., fraction of time in a slot to be accessed by node i) and T is the size of frame. Time slot share t_i is the strategy of nodes. Two nodes $i = 1, 2$ transmit their data without

TABLE II

SUMMARY OF TDMA-BASED CHANNEL ACCESS GAMES

Game model	Key concept	Method of solution	Reference
Noncooperative static game	Nodes minimize the time slot usage given the channel power gain.	Convex optimization	[23]
Auction game	Time slot allocation with a second-price auction scheme when a fraction of time to relay data is used as bid	Distributed bid update algorithm	[25]
	Time slot allocation with a second-price auction scheme when money is used as bid	Fair and efficient centralized opportunistic scheduler	[26]
Dynamic game	Channel competition and rate control in TDMA cognitive radio formulated using Markov game theory	Value iteration algorithm	[27]
		Iteration correlated algorithm and correlated Q-learning algorithm	[28]
Repeated game	Nodes choose their power allocation under power constraint and channel condition. To enforce node cooperation, a punishment and truth-telling mechanism is used.	Self-enforcing truth-telling mechanism	[29]

collision if $t_1 + t_2 \leq 1$ and collision occurs if $t_1 + t_2 > 1$. Time slot allocation to the nodes is shown in Fig. 1(a). Since the nodes have self-interest, they minimize the time slot usage given the channel state information (i.e., channel power gain denoted as h_i) subject to the effective capacity [24]. The corresponding optimization formulation for node 1 is as follows:

$$\min_{t_1} \mathbf{E}_h\{t_1\} \tag{4}$$

subject to

$$\mathbf{E}_h\{e^{-\beta_1 t_1 R_1}\} - A_1 \leq 0 \tag{5}$$

and

$$t_1 \leq 1 - t_2 \tag{6}$$

where $\mathbf{E}_h$ denotes expectation over h, β_1 is the normalized QoS exponent, R_1 is the normalized transmission rate which is a function of channel state information. A_1 is equal to $e^{-\theta_1 C_1}$ where C_1 denotes the target effective capacity exponent and θ_1 denotes the QoS exponent for node 1. This effective capacity is also considered as an objective of the system. Nash equilibrium is the solution of this time slot competition game. It is found that the Nash equilibrium may not be unique. However, since the game can be formulated as a convex optimization problem, a unique solution can be obtained by minimizing the Lagrangian function of the objective function if the available time slot length is enough to guarantee QoS for both the nodes.

2) Auction game-theoretic approach: In [25], a second price and sealed bid auction for time slot competition in a dynamic spectrum access scenario is proposed. In dynamic spectrum access, each node $i \in \mathbb{I} = \{1, \ldots, M\}$ (i.e., the bidder/player in a game) submits its bid to the base station. The value of the submitted bid is the portion of the time slot (i.e., between 0

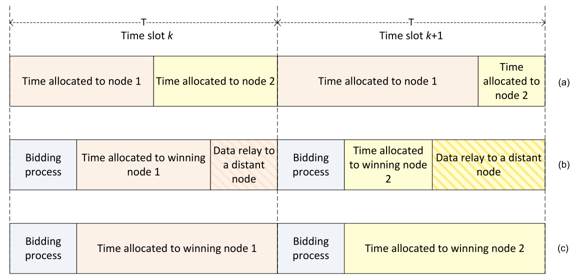

Fig. 1. The diagram represents different time slot allocations: (a) time slot allocation based on [23], (b) time slot allocation based on [25], and (c) time slot allocation based on [26].

and 1) that will be used to help the base station relaying data to another distant node. The bidding value b_i of node i is a non-decreasing function of the channel condition x_i. The base station (i.e., the auctioneer) allocates the downlink channel to a node offering the highest bid (as shown in Fig. 1(b)). The price that this winning node pays is equal to the second highest bid. The amount of transmitted data of winning node j is denoted as $d_j = x_j(1 - \max_{i \in \mathbb{I}, i \neq j} b_i(x_i))$, where x_j is the channel condition of the winning node which is assumed to be the amount of data received per unit time, and $b_i(x_i)$ is the bid submitted by a node. A node chooses a value of bid which maximizes its expected amount of data transmitted under its budget constraint given the probability distributions of the channel conditions of all the nodes. The budget constraint of node i represents the amount of time that the node is able to provide to the base station for data relaying. Nash equilibrium is considered as the solution. It is found that, for pure strategy, a Nash equilibrium exists in the two-node case, but in a general multiple-node case, a Nash equilibrium may not exist. A distributed algorithm is proposed for updating the bids which converges to the Nash equilibrium. The results show that to avoid zero throughput (i.e., maximum bid), the budget constraint has to be smaller than one. Also, the higher the budget constraint, the lower is the throughput for each node.

A system model almost similar to that in [25] is considered in [26]. The second-price auction mechanism is used for the nodes competing for time slots in a downlink transmission scenario. Similar to [25], the utility function of a node is the expected amount of data transmitted and the bidding value b_i of node i is a function in the channel condition x_i. A node submits a bid which maximizes its expected amount of data transmitted under the budget constraints given the probability distributions of the channel conditions of all the nodes. The time slot allocation process for this auction game can be illustrated as in Fig. 1(c). The Nash equilibrium is considered as a solution. It is shown that the Nash equilibrium leads to a unique allocation which is also Pareto optimal. For uniformly distributed channel state, the aggregated throughput that nodes achieve at the Nash equilibrium is at least 3/4 of the optimal aggregated throughput achieved using an optimal centralized allocation without fairness consideration. Also, a centralized opportunistic scheduler is proposed to achieve proportional fairness. The *a priori* knowledge of channel distribution is not required by this scheduler. The centralized scheduler will assign time slots according to the Nash equilibrium strategy.

3) Dynamic game-theoretic approach: In [27], a Markovian dynamic game is formulated to solve the transmission rate adaptation problem in a dynamic spectrum access-based cognitive radio network. In a cognitive radio network, the secondary users (or cognitive radio users) opportunistically access the radio spectrum, which is licensed to the primary (or licensed)users, without causing harmful interference to the primary users. The players of the game are secondary nodes competing for the channel or time slot in a TDMA scenario (e.g., in IEEE 802.16-based network). In a TDMA cognitive radio system, the system has a predefined decentralized access rule that allows only one secondary node to access the channel at a time. The access rule is defined as a function of channel quality and transmission delay. This transmission rate control problem is formulated as a general-sum switching control Markovian dynamic game.

In this dynamic game, the system state transition probability at each time slot depends only on the active secondary node. Node i (i.e., secondary node i) follows a decentralized access rule to try to occupy a time slot at time n after a period of time $t_i^n = \frac{\gamma_i}{q_i^n h_i^n}$ where γ_i is the QoS parameter of node i, q_i^n is the buffer occupancy state of user i, and h_i^n is the channel state of node i. The composite variable $\mathbf{x}_i^n = [q_i^n, h_i^n]$ denotes the state of user i at time n. If there are more than one nodes having the same waiting period, a node will be randomly picked with equal probability. After node j is selected to transmit data, this node chooses action a_j^n (i.e., transmission rate in bits/symbol) assuming an M-ary quadrature amplitude modulation. The transmission cost of the selected node j, $c_j(\mathbf{x}^n, a_j^n)$, is defined as its transmission bit error rate (BER), and the cost of node i, $d_i(\mathbf{x}^n, a_j^n)$, is defined as its delay constraint (i.e., QoS constraint) which is a function of the buffer state q_i^n. The transition probabilities depend only on the action of active node; hence, a Markovian dynamic game can be formulated. The strategy of node i denotes the transmission policy s_i. The Nash equilibrium policy s_i^* is computed by minimizing the expected total discounted cost function subject to the expected total discounted delay constraint as follows:

$$s_i^{*(n)} = \{s_i^n : \min_{s_i} C_i^n(s_i)\} \quad \text{subject to} \quad D_i^n(s_i) \leq \hat{D}_i \tag{7}$$

where $C_i^n(s_i)$ is the infinite expected total discounted transmission cost calculated from $c_j(\mathbf{x}^n, a_j^n)$. $D_i^n(s_i)$ is the infinite expected total discounted delay which is calculated from $d_i(\mathbf{x}^n, a_j^n)$ and cannot be greater than threshold $\hat{D}_i$.

The value iteration algorithm is used to obtain a Nash equilibrium policy. The Nash equilibrium policy of any node i is observed to be a randomized mixture of pure policies and the pure policies are non-decreasing on the buffer occupancy state. A stochastic approximation algorithm exploiting this structure is presented to efficiently estimate the Nash equilibrium policy by computing parameters such as buffer state thresholds and randomization factors.

In [28], a system model similar to that presented in [27] is considered; however, correlated equilibrium is studied as the solution of the game. Two distributed correlated equilibrium algorithms (i.e., iterative correlated equilibrium algorithm and correlated Q-learning algorithm) are proposed to obtain the correlated equilibrium in the Markovian game. The stationary policy $\mathbf{s}^*$ is a correlated equilibrium for the Markovian game, i.e.,

$$\sum_{\mathbf{a}_{-i} \in A_{-i}} s^*_{\mathbf{x}}(\mathbf{a}_{-i}, a_i) Q_i^{\mathbf{s}^*}(\mathbf{x}, \{\mathbf{a}_{-i}, a_i\}) \geq \sum_{\mathbf{a}_{-i} \in A_{-i}} s^*_{\mathbf{x}}(\mathbf{a}_{-i}, a_i) Q_i^{\mathbf{s}^*}(\mathbf{x}, \{\mathbf{a}_{-i}, a_i^{'}\}) \tag{8}$$

where $Q_i^{\mathbf{s}^*}(\cdot)$ is the Q-function of user i which is the total discounted reward of taking action $\mathbf{a}$ in state $\mathbf{x}$. The Q-function is a function of the user i's utility plus the infinite expected total discounted utility. The utility is the difference between a function of achievable transmission rate and the transmission delay. When an iterative algorithm is used to find the correlated equilibrium, each user does not need the information of the Q-functions of other users, and this can be used to develop distributed algorithm. However, the probability transition matrix is required to update the Q-function values. The correlated Q-learning algorithm can remove the requirement of a system state transition probability matrix for the iterative correlated equilibrium. Hence, it is more practical than the iterative algorithm.

4) Repeated game-theoretic approach: In [29], a repeated game model for spectrum sharing in a cognitive radio network is presented. The game enforces the nodes to tell their true channel conditions and to cooperate with each other. Data transmission over a long time period is considered. Therefore, spectrum sharing can be formulated as a repeated game where the nodes are concerned about their payoffs (e.g., throughputs) in the future. The actions of the nodes are the power allocation according to the power constraint and channel condition. In this game, the power constraint is assumed to be identical for all nodes. If all the nodes make an agreement and share the spectrum in an orderly fashion, every node gains benefit from the cooperation. However, some nodes may violate the agreed upon rule and deviate from cooperation. Then, the game model provides a punishment mechanism which will be triggered and applied to the deviating node for a certain period of time. The period of time for punishment is chosen such that the expected payoff from cooperation is greater than the expected payoff from deviation.

To design a cooperation rule, an opportunistic time slot allocation method is developed which maximizes the total throughput. The node informing the best channel gain will be allocated time slots for transmission. However, in the incomplete information case, the channel gain of one node may not be known to other nodes, and some node may falsely inform its channel gain information. Therefore, a Bayesian mechanism is introduced to enforce all the nodes to tell the true values of their channel gains.

TABLE III

SUMMARY OF FDMA-BASED CHANNEL ACCESS GAMES

Game model	Key concept	Method of solution	Reference
Noncooperative game	Channel allocation among nodes equipped with multiple radio interfaces to obtain system-wide throughput optimality	An algorithm to obtain a strongly dominant strategy equilibrium (SDSE) [31]	[30]
	Sub-channel allocation by allocating transmission rates on different channels subject to power constraint and required rate	A mechanism called virtual referee is used to reduce the complexity of the game.	[32]
	Channel allocation among nodes equipped with multiple radio interfaces when rate on each channel is allocated equally by time-division schedule	A centralized algorithm with perfect information, a distributed algorithm with perfect information, and a distributed algorithm with imperfect information	[33]
	Sub-channel assignment and power allocation when multiple base stations are players instead of mobile nodes	A distributed algorithm based on a greedy approach for sub-channel assignment problem and base on the best-response update for power allocation problem	[34]
	Channel allocation of secondary nodes when transmission power is constrained. The game is also extended to a Stackelberg game.	N/A	[35]
Auction game	Power is allocated based on water-filling allocation according to the result from the second-price auction.	An iterative update algorithm based on bidding efficiency and the subgradient algorithm	[36]
Cooperative game	Coalition formations among secondary base stations to improve knowledge of available channels to serve secondary nodes	A distributed algorithm to find a Nash-stable set of coalitions	[38]
	Transmission power allocation and subchannel assignment using coalitional game when a player is a pair of one subchannel and one node	An iterative algo. to update best-responses based on Markov modeling	[40]

B. Channel Access Games in FDMA

In FDMA, the nodes compete for available channels in the network and the solutions of the game models (i.e., equilibrium) can be obtained in the complete and incomplete information cases. We consider three different game models, namely, *noncooperative static game*, *auction game*, and *cooperative game* models. A summary of the key features of these game models for FDMA is provided in Table III. The details of these models are discussed next.

1) Noncooperative static game-theoretic approach: In [30], the optimal FDMA channel assignment problem for noncooperative wireless networks is studied assuming that the nodes can be equipped with either single or multiple radio interfaces. The available frequency band is divided into orthogonal channels. The authors introduce a payment formula to ensure the existence of a strongly dominant strategy equilibrium (SDSE) [31], which is a stronger solution concept than the Nash equilibrium. This payment is used to obtain the globally optimal solution in terms of effective system-wide throughput. The strategy of node i (s_i) is the channel assignment vector which is the number of radio interfaces allocated to each channel. The solution in terms of SDSE can be described as follows:

$$\forall \mathbf{s_{-i}} \in \mathbb{S}_i, \forall s_i \neq s_i^*, u_i(s_i^*, \mathbf{s_{-i}}) \geq u_i(s_i, \mathbf{s_{-i}}) \tag{9}$$

$$\exists \mathbf{s_{-i}} \in \mathbb{S}_i, \forall s_i \neq s_i^*, u_i(s_i^*, \mathbf{s_{-i}}) > u_i(s_i, \mathbf{s_{-i}}) \tag{10}$$

where $\mathbb{S}_i$ is the set of all possible strategies and $u_i(\cdot)$ is the payoff function of node i. The payoff function is defined as the difference between the throughput and the payment to the system administrator. The payment is a function of the node's throughput plus a penalty (if the node deviates from the globally optimal solution) or a bonus (if the node does not deviate). An algorithm to obtain the SDSE is proposed. It is proved that the algorithm converges to the SDSE.

Multiple channel access in multi-cell and multi-user OFDMA networks is considered in [32]. In multi-cell networks, changes of resource allocation in a cell affect the performances of other nearby cells. A noncooperative game model for sub-channel assignment, rate adaptation, and power control is introduced. Node i with self-interest maximizes its own payoff $u_i(\cdot)$ (e.g., minimizes its transmission power) by allocating its transmission rates $\mathbf{r}_i$ on different sub-channels $k \in \{1, \ldots, K\}$ under the required rate R_i and power constraint P^i_{max} as follows:

$$\min_{\mathbf{r}_i} u_i(\cdot) = \sum_{k=1}^{K} P_i^k, \qquad \text{s.t.} \quad \sum_{k=1}^{K} r_i^k = R_i \tag{11}$$

where P_i^k is the transmission power of user i in subchannel k.

Nash equilibrium is considered as a solution. This Nash equilibrium (NE) can be obtained by using the water filling algorithm. However, in some cases of high channel interference, there might be multiple Nash equilibria or the solution might also be undesirable (i.e., the overall power for the users is larger than the power constraint: $\sum_{k=1}^{K} P_i^k > P^i_{max}$). A dual noncooperative game is used if the desired NE solution cannot be obtained. The definition of the dual game is as follows:

$$\max_{\mathbf{r}_i} \sum_{k=1}^{K} r_i^k, \text{s.t.} \sum_{k=1}^{K} P_i^k = P^i_{max}. \tag{12}$$

After the dual noncooperative game converges, if the desired NE solution is still not reached (i.e., if any node has to play the dual noncooperative game, the obtained NE is considered as an undesired NE), a mechanism called virtual referee is introduced to improve the performance of this noncooperative game.

The key idea of the virtual referee mechanism is that a referee monitors the nodes in the network. If the Nash equilibrium is reached, the referee does nothing; however, if it is not, the referee will modify the game rule in order to remove some nodes from accessing subchannels so that a better performance can be achieved. The flow of this noncooperative game with a referee is shown as Fig. 2.

A channel allocation game is studied in [33] as a static game when nodes have multiple radio interfaces . The players are the nodes with self-interest which aim to maximize their own profits defined as the total rates or channel utilization. In this

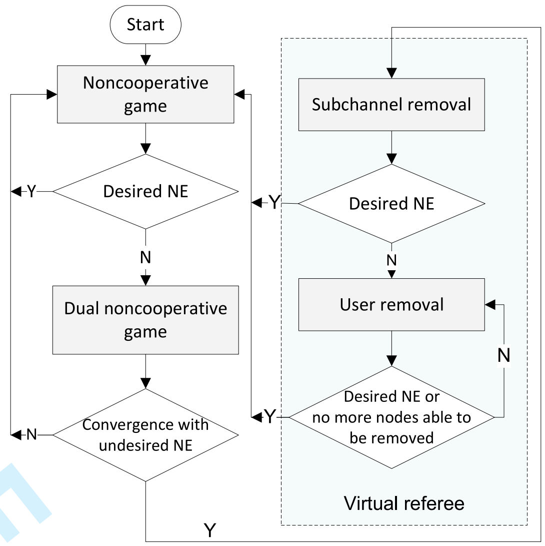

Fig. 2. The diagram illustrates the steps of the algorithm for noncooperative game with virtual referee in OFDMA networks.

game, there are K orthogonal channels. If the same channel is used by multiple nodes, they can hear the transmissions of each other. Moreover, a node can use multiple channels at the same time. The strategy of each node is the channel allocation vector or the number of radio interfaces on each channel. The payoff of each node is the achieved bit rate. It is assumed that the rate on each channel is allocated equally by using a reservation-based time-division schedule among the interfaces. The total available rate on a channel is assumed to be a non-increasing function of the number of radio interfaces accessing this channel. The set of channels used by node i is denoted as $\mathbb{K}_i$. The payoff function of node i, defined as u_i, is the sum of achieved bit rate r on each occupied channel $k \in \mathbb{K}_i$ as follows:

$$u_i = \sum \frac{l_{i,k}}{l_k} R(l_k) \tag{13}$$

where $l_{i,k}$ is the number of radio interfaces of node i currently using channel k, l_k is the number of radios using channel k, and $R(l_k)$ is the total rate which is a decreasing function of the number of radios using channel k.

Nash equilibrium is considered as a solution. If the total number of radio interfaces is smaller than or equal to the number of channels, then a flat channel allocation (not more than one radio interface per channel) is the Nash equilibrium. To find a Nash equilibrium, three algorithms are introduced. The first one is a centralized algorithm with perfect information. It requires sequential action of players and global coordination. This global coordination can be achieved with an extra radio interface per device for scanning the channels. The second algorithm is a distributed algorithm with perfect information. This algorithm is a round-based algorithm in which a random radio interface assignment to the nodes over the channels is used. It is assumed that there is no node that can assign more than one radio interface to any channel. After the initial assignment, each node evaluates the number of radio interfaces on each channel and tries to improve its total rate by reorganizing the allocation. However, an unstable allocation can occur. To avoid this problem, a backoff technique is used. Each node chooses a random initial value and then decreases this counter value periodically. The reallocation is performed when the counter is zero.

The third algorithm is a distributed algorithm with imperfect information. This algorithm also uses the backoff technique. In each round, a node calculates the average number of devices on the channels. Then, the node can obtain a probability to choose channel. The algorithm can reach a stable state but it may not be the Nash equilibrium since the available local information is incompletely known. Then, a mechanism is introduced to resolve inefficient stable states.

The main difference of [34] from the previous game model is that the base stations (rather than the mobile nodes) are the players in this game. A noncooperative distributed resource allocation game in a multi-cell OFDMA system is proposed for M base stations serving L nodes. All of the base stations share the same frequency band with the total bandwidth B divided into K sub-channels. The players are the base stations and a strategy is the sub-channel assignment and power allocation. The transmission power at a sub-channel k of base station i is denoted as p_k^i. That is, $\mathbf{p}^i = (p_1^i, \ldots, p_k^i, \ldots, p_K^i)$ is the transmission power vector of all the sub-channels of base station i. The constraint on the transmission power of each base station is $\sum_{k=1}^{K} p_k^i \leq P_{max}$. The payoff function is defined as the difference between the weighted sum of the data rates ($\sum_{j \in \mathbb{U}_i} \beta_j R_j(\mathbf{P}, \mathbf{A^i})$) and the cost of total power ($\sum_{k=1}^{K} p_k^i$) where $\mathbb{U}_i$ is the set of nodes in cell i, β_i is a weighting factor, $\mathbf{P} = [\mathbf{p}^1, \ldots, \mathbf{p}^i, \ldots, \mathbf{p}^M]$ and $\mathbf{A}^i = [a_{kj}^i]_{K \times L}$, a_{kj}^i is 1 if sub-channel k is assigned to node j; otherwise, it is 0. The payoff function is defined as follows:

$$u_i(\mathbf{P}, \mathbf{A^i}) = \sum_{j \in \mathbb{U}_i} \beta_j R_j(\mathbf{P}, \mathbf{A^i}) - c \sum_{k=1}^{K} p_k^i. \tag{14}$$

where c denotes the price per unit power, having the unit bps/W.

Each base station maximizes its payoff function. To find the optimal sub-channel assignment given a network power vector $\mathbf{P}_0$, the sub-channel assignment game can be represented as $\max_{\mathbf{A}^i} \sum_{j \in \mathbb{U}_i} \beta_j R_j(\mathbf{P}_0, \mathbf{A}^i)$. Using a greedy approach, the solution $\mathbf{A}^{*i}(\mathbf{P})$ can be found when $\mathbf{P}$ is determined. Hence, we can obtain the optimal power allocation, which is the Nash equilibrium, by solving $\max_{\mathbf{p}^i} \sum_{j \in \mathbb{U}_i} \beta_j R_j(\mathbf{P}_0, \mathbf{A}^{*\mathbf{i}}(\mathbf{P}))$. The existence and uniqueness of Nash equilibrium of the power allocation game can be proved. Moreover, a distributed resource allocation algorithm is proposed to obtain both the sub-channel assignment and power allocation. The algorithm iteratively converges to an equilibrium point. The key concept of the algorithm is that each base station updates the sub-channel assignment according to a greedy approach and the power allocation according to the best-response update using local information from nodes (i.e., SINR in each sub-channel).

The work of [35] presents a noncooperative game model for spectrum access in distributed cognitive radio networks. In such a network, M secondary nodes opportunistically transmit data on the channel allocated to the primary node. Let p_i be transmission power of secondary node i (i.e., transmitter and receiver). Secondary node i has a maximum transmission power constraint ($p_i \leq \hat{p}_i$) in each channel. It is assumed that the total power in each channel must not exceed the maximum total power of all users using the channel $k \in \{1, \ldots, K\}$, which is $\sum_{i \in \mathbb{U}_k} p_i \leq \hat{\mathbf{P}}$ where $\mathbb{U}_k$ denotes the set of all nodes using channel k and $\hat{\mathbf{P}}$ is the maximum total power of all users.

The strategies of secondary nodes are the choices among K available channels. The objective of secondary node i is to maximize its payoff, which is a function of SINR γ_i^k on each channel k (i.e., $\max u_i(\gamma_i^k)$) subject to the maximum transmission power constraint $\hat{p}$ (i.e., $p_i \leq \hat{p}$). Using an N-channel bi-matrix game, the existence of pure strategy Nash equilibrium is proved. Next, this noncooperative game model is extended to the Stackelberg game since the channel access of a disconnecting secondary node depends on the other secondary nodes' strategies. There are the events that make the channel access disrupted. Arrival of a primary node is the main cause of channel access disruption since the secondary node has to leave the channel immediately. Interference from multiple secondary nodes accessing the channel and channel fading may also cause disruption in channel access.

In an unexpected event, a secondary node who has any strategy that can help uninterrupted channel access is considered to be a leader (i.e., a leader has information on channel access by primary users). The rest of secondary nodes who do not have any information on accessing channel are followers. Then, the payoff of the leader is the summation of $u_i(\gamma_i^k)$ and the cost that the followers pay for switching the channel. The payoff for a follower is the difference between $u_i(\gamma_i^k)$ and the price that the leader sets for switching the channel. Note that this leader-follower scenario is temporary. A node finds a channel and broadcasts the new channel information. Only one node can be a leader in each channel. The numerical results show the existence of an equilibrium solution.

2) Auction game-theoretic approach: In [36], a distributed resource control scheme is presented to achieve fairness in OFDMA systems. Specifically, an auction game-theoretic resource allocation scheme based on iterative multi-unit second price auction is applied. A base station (BS) controls transmission power and bidding to maximize system capacity and node fairness. From an information-theoretic point of view, the medium access control (MAC)-layer throughput capacity region is achievable by successive decoding [37] when at each subchannel k, the first node's decoded signal is subtracted from the sum signal, then the next node's signal is decoded, and so on.

In this auction, first each node i submits bid b_i which includes power control variable and bid value. Each node calculates its bid by maximizing the expected Shannon capacity, and each node submits its bid and waits to be assigned the decoding priority for each sub-channel from the base station. After the bids are received by the base station, the decoding priority is assigned to each node following the weighted sum-rate capacity maximization of the base station. The cost that each node i

pays is the cost for winning the lth decoding priority at subchannel k. Then, transmission power will be allocated based on the optimal and fair water-filling allocation according to the result of the decoding order. Also, the cost that the nodes have to pay will be announced.

To obtain the Nash equilibrium for bidding in this auction, an iterative update algorithm is proposed. The key concept is to update the bid value based on the difference between the current bidding efficiency and the target bidding efficiency at each time slot t. Bidding efficiency is computed by a node's achievable transmission rate divided by the cost of the node. Also, the bidding control variable is updated using the subgradient algorithm as follows:

$$x^{(t+1)} = x^{(t)} + \alpha_t g^{(t)} \tag{15}$$

where $x^{(t)}$ is the bidding control variable at time t, α_t is a constant step size, and $g^{(t)}$ is a subgradient which is a function of the total cost that node has to pay for and the total bid money that node can use during the game. The analytical and simulation results show that this iterative update algorithm can converge to the stable and optimal equilibrium which can achieve fairness among users when the channel conditions of the subchannels for the different nodes are uniformly distributed.

3) Cooperative game-theoretic approach: In [38], a cooperative game theoretic model is proposed for secondary base stations (SBSs) in a cognitive radio network. The main concept of this work is to form cooperative groups among the SBSs in a multi-channel cognitive radio network by using a game theoretic approach called coalition formation game. To improve the quality of information about availability of primary nodes (PNs) to serve secondary nodes (SNs), the SBSs share their information through control channels such as a cognitive pilot channel (CPC) to other SNs. SBS $i \in \mathbb{I} = \{1, \ldots, M\}$ detects the presence of any PU $k \in \mathbb{K} = \{1, \ldots, K\}$ by using a channel and serves L_i SNs. Each SBS can gather information on the availability of channels as a subset $\mathbb{K}_i \subseteq \mathbb{K}$. The false alarm probability obtained by SBS i over PN channel k is denoted as $P^i_{fal,k}$. Then, the total potential utility of SBS i in a noncooperative approach is given as follows:

$$u(\{i\}) = \sum_{k \in K_i} \sum_{j=1}^{L_i} [(1 - P^i_{fal,k})\theta_k \rho_{ji} - \alpha_k (1 - P^i_{det,k})(1 - \theta_k)(\rho_{kr_k} - \rho^j_{kr_k})] \tag{16}$$

where ζ_k is the probability that channel k is available and α_k is a penalty factor defined by PN k for any SN causing interference. The term $(1 - P^i_{det,k})$ is the probability of mis-detection. ρ_{ij} is the probability of successful transmission of SN j to its serving SBS i at the time when channel k is available. The term $(\rho_{kr_k} - \rho^j_{kr_k})$ is the reduction in the probability of successful transmission of PN k at its receiver r_k whenever SN j transmits over channel k at a time of the presence of PN k due to the mis-detection of PN k.

To improve the utility, the SBSs can share the available knowledge of the presence of PNs; however, there is a tradeoff between the utility gained from learning new channels (through information sharing) and the cost to obtain cooperative information. In a coalition $\mathbb{S}$, the set of known PNs by any SBS i in the coalition is defined as $\mathbb{K}_{\mathbb{S}} = \cup_{i\in\mathbb{S}}\mathbb{K}_i$. Hence, the payoff of any SBS $i \in \mathbb{S}$ is defined as follows:

$$u_i(S) = \sum_{k\in\mathbb{K}_{\mathbb{S}}} \sum_{j=1}^{L_i} [(1 - P^{i_k}_{fal,k})\theta^k_{ii_k}\rho_{ji} - \alpha_k(1 - P^{i_k}_{det,k})(1 - \theta^k_{ii_k})(\rho_{kr_k} - \rho^j_{kr_k})] \tag{17}$$

where $\theta^k_{ii_k}$ is the probability that SBS i can obtain the knowledge of channel k from another SBS $i_k \in \mathbb{S}$. $i_k = i$ if SBS i has its own information on channel k. SBS i_k giving the maximum utility will be selected by SBS i. Since the payoff of SBS i depends only on the identity of the SBSs in the coalition which SBS i is a member of, this game can be considered as a hedonic coalition game [39]. The formulation of the game is described next.

Given two coalitions $\mathbb{S}_1$ and $\mathbb{S}_2$, and $i \in \mathbb{S}_1$ and $i \in \mathbb{S}_2$, $\mathbb{S}_1 \succeq \mathbb{S}_2$ means SBS i prefers to be a member of coalition $\mathbb{S}_1$ over being a member of coalition $\mathbb{S}_2$, and $\mathbb{S}_1 \succ \mathbb{S}_2$ means SBS i strictly prefers to be a member of coalition $\mathbb{S}_1$ over being a member of coalition $\mathbb{S}_2$. Then, the proposed coalition formation game can be defined as follows:

$$\mathbb{S}_1 \succeq \mathbb{S}_2 \Leftrightarrow w_i(\mathbb{S}_1) \geq w_i(\mathbb{S}_2) \tag{18}$$

where $w_i(\mathbb{S})$ is a preference function for SBS i and coalition $\mathbb{S}$. SBS i makes a decision to leave its current coalition $\mathbb{S}_x$ and then join another coalition $\mathbb{S}_y$ when $\mathbb{S}_x \neq \mathbb{S}_y$ if and only if $\mathbb{S}_y \cup \{i\} \succ_i \mathbb{S}_x$. This can be interpreted as that an SBS will switch to a new coalition if it can strictly gain more payoff without decreasing other members' payoffs in the new coalition. A partition or a set of all coalitions is Nash-stable if no SBS has an incentive to move from its current coalition to another coalition or to deviate and act alone. A distributed algorithm to find a Nash-stable partition is proposed and the simulation results show that the average payoff per SBS of the coalition formation scheme outperforms one of the noncooperative schemes when the number of SBS increases.

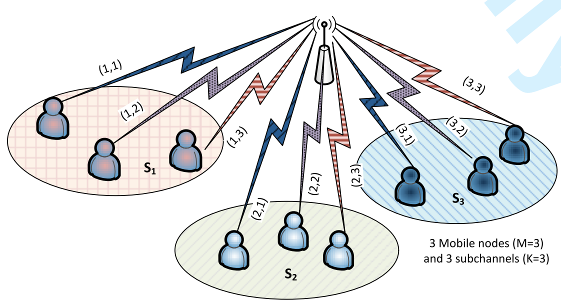

Fig. 3. Coalitions of players are formed following the game model in [40] when there are 3 mobile nodes and 3 subchannels.

Another coalitional game for transmission power allocation and subchannel assignment in the uplink channel of an OFDMA system is presented in [40]. In the considered system model, there are M nodes located in the coverage area of a same base station. The base station provides K subchannels to node $i \in \mathbb{I} = \{1, \ldots, M\}$ to guarantee the target rate requirement. Let k

denote each subchannel $k \in \mathbb{K} = \{1, \ldots, K\}$. Let R_i be the target rate requirement of node i. Suppose that the total bandwidth is B, then the carrier spacing of every subchannel is $\triangle f = B/K$. A player defined in this game is a pair of one subchannel and one node. Hence, MK players are considered in this game. The strategy of each player is the transmission power assigned to subchannel p_{ik}. Then, there are M coalitions $\zeta = [\mathbb{S}_1, \ldots, \mathbb{S}_i, \ldots, \mathbb{S}_M]$ to be assigned to the M nodes and each coalition $\mathbb{S}_i$ contains K players (e.g., shown in Fig. 3).

In this game, the members in each coalition do not change during the game. Consequently, the coalition $\mathbb{S}_i$ achieves its rate $C_i = \sum_{k \in \mathbb{K}} C_{ik}$ where $C_{ik} = \triangle f \log_2(1 + \gamma_{ik})$ is the Shannon capacity achieved by node i on subchannel k. γ_{ik} is the SINR at the base station. The payoff that each coalition will obtain is defined as follows:

$$u(\mathbb{S}_i) = \frac{1}{C_k/R_k - 1} - \alpha.t(1 - C_k/R_k) \tag{19}$$

where $t(\cdot)$ is the step function with $t(y) = 1$ if $y \geq 0$ and $t(y) = 0$ if $y < 0$, and α is a positive constant. A coalition will achieve the highest payoff (i.e., positive infinite) when $C_k = R_k$. An iterative algorithm based on Markov modeling of the TU coalitional game is proposed to update the best-responses. The analytical and numerical results show that the algorithm can be considered as a Markov process. The process can quickly converge to an absorbing state which is also a Nash equilibrium solution with probability of one.

C. Channel Access Games in CDMA

CDMA systems use spread-spectrum technology in which each node is assigned with a different code to allow multiple users to be multiplexed over the same channel at the same time. Power control for multiple access is crucial for CDMA to ensure that the received signal can be decoded correctly. In a CDMA system with self-interested nodes, the transmission power control problem can be modeled as both the complete and incomplete information noncooperative games. Also, cooperative game models can be used for group-rational nodes in a CDMA system to achieve a Pareto optimal power control strategy. A summary of the key features of these game models for CDMA is provided in Table IV. The details of these models are discussed next.

1) Noncooperative static game-theoretic approach: In [41], a noncooperative game model is presented for power control. Each node has an objective to maximize its own utility. The game considers a multi-carrier direct-sequence CDMA system in which the data stream for each node is divided into multiple parallel streams. Each stream is first spread using a spreading sequence and then transmitted on a carrier. The strategy of each node is to choose its transmission power. A high transmission power may yield high SINR and high transmission rate. However, it may also cause high interference to the other nodes in the network. The utility of a node is defined as the ratio of the total throughput and the total transmission power for all K

TABLE IV

SUMMARY OF CDMA-BASED CHANNEL ACCESS GAMES

Game model	Key concept	Method of solution	Reference
Noncooperative game	Nodes choose transmission power for all carriers when their optimal SINRs are taken into consideration.	An iterative best-response update algorithm	[41],[42]
	Power control game when nodes can adjust the processing gain in a multirate CDMA system	N/A	[43]
	The game considers both rate and power control for the uplink CDMA systems.	An NRPG algorithm when the information of interference plus noise is required	[44]
	Nodes choose transmission power based on their objective to minimize cost.	A distributed SIR-based power update algorithm	[47]
Cooperative game	Nodes minimize power consumption while satisfying the SINR requirements.	N/A	[48]

carriers.

Assuming that all the nodes use equal transmission rates, the utility function of a node can be expressed as the ratio of the summation of the efficiency functions and the summation of transmission powers for all K carriers. The efficiency function ($f(\gamma)$) represents packet success probability. The utility is a non quasi-concave function of the transmission power of the node. Nash equilibrium is considered as a solution. At the Nash equilibrium, each node transmits only on the carrier with the best effective channel. This best effective channel is the channel that requires the least amount of transmission power to achieve optimal SINR γ^* at the output of the uplink receiver. Optimal SINR $\gamma^* = \gamma f^{'}(\gamma)$ is the solution to the efficiency function. The unique Nash equilibrium in this game can be achieved under a certain set of conditions.

To this end, an iterative and distributed algorithm based on best-response update is proposed to obtain the Nash equilibrium. The results show that at the Nash equilibrium, the total network utility of this multicarrier system is higher than that of a single carrier system. Also, it is higher than that of a multicarrier system with the nodes choosing their transmission powers to maximize their utilities over each carrier independently.

In [42], a noncooperative static Bayesian game is presented for uplink power control in a CDMA network. Each node chooses its transmission power. The payoff is a function of the difference between throughput and power consumption. The throughput part in the payoff function is composed of the gain from achievable bit rate and a 'success function'. The 'success function' is a Sigmoid function of SINR. Since the path loss information for the other nodes is not completely known, each node uses path loss probability density functions to estimate the SINR (and hence payoff) of the other nodes.

The solution of this incomplete information game is the Bayesian Nash equilibrium (BNE), which can be obtained from the best-response dynamics. This dynamics represents the strategy update rules based on the expected utility when path loss information is not completely known to the other nodes. The existence of the Bayesian Nash equilibrium is proved and it can be obtained in a distributed way.

In [43], a noncooperative power control game for multirate CDMA networks is studied. All nodes in this multirate CDMA system use the same chip rate. However, they are able to adjust their processing gains to increase their data rates. The objective of the game is similar to that of [41], [42]. However, the payoff of each node is defined as the difference between the throughput in bits per second and the cost of transmission power. The cost that each node has to pay is the function of its received power divided by the total received power of all nodes plus noise at the base station. The existence and uniqueness of the Nash equilibrium are proved for two channel models, i.e., a binary-input Gaussian output channel and a binary symmetric channel. Also, the spectral efficiency is derived for both the channel models.

A joint rate and power control game model is presented in [44] for the uplink CDMA communications. The system model and the concept of power control and rate updates in this game are similar to those in [46]. In particular, each node can adjust both transmission rate and transmission power to maximize its payoff (i.e., utility). The payoff of each node is in bits/J, which can be calculated from packet length, transmission power, transmission rate, and an efficiency function which is related to the SINR. The strategy of each node is to choose rate and power for transmission. The sets of rate and power are shown to be convex. The existence of Nash equilibrium for joint rate and power control is proved by using the Nikaido-Isoda theorem [45]. Moreover, an algorithm to find the Nash equilibrium in this non-cooperative joint transmission rate and power control game, shortly called NRPG, is proposed. The requirement of this algorithm is that each node has to obtain the SINR of the other nodes. The algorithm is proved to converge to the same Nash equilibrium when the nodes are assigned with different initial powers. Also, NRPG can converge to the solution faster than the algorithm proposed by Zhao and Lu [46].

Another noncooperative game model for power control is proposed in [47]. The strategy of each node is to choose transmission power p_i. Each node in this system model has an objective to minimize its cost (instead of maximizing its utility). The cost function should be convex and non-negative and in [47] it is chosen to be a weighted sum of power ($\beta_i p_i$) and square of SIR error ($\delta_i(\gamma_i^{tar} - \gamma_i)$) which is the difference between the actual SIR and the target SIR. β_i and δ_i are weighting constants. A distributed algorithm is proposed to obtain the Nash equilibrium. The power update algorithm is expressed as follows:

$$p_i^{t+1} = \gamma_i^{tar} \left(\frac{p_i^t}{\gamma_i^t} \right) - \frac{\beta_i}{2\delta_i} \left(\frac{p_i^t}{\gamma_i^t} \right)^2 \tag{20}$$

where t denotes the t^{th} iteration of the algorithm. However, the information of interference power and SIR is still required by the node from the base station in order to calculate γ_i^t in each iteration. The convergence of the algorithm is proved. The proof shows that the algorithm converges to a unique fixed solution under a set of conditions. Also, the proposed algorithm outperforms the traditional power balance algorithm (e.g., smaller number of iterations are required for convergence to a solution, higher efficiency in power saving, and more nodes can be handled).

2) Cooperative static game-theoretic approach: In [48], a cooperative game is applied to obtain the optimal power allocation in a CDMA system. A multiuser CDMA system with perfectly known channel information and fixed signature and linear sequences is considered. The objective is to minimize power consumption given minimum SINR of each node. It is shown that the power region (i.e., a feasible set of power allocation such that the SINR requirement of each node is met) is convex and log-convex. If the power region is not empty, then there is a unique power allocation that satisfies the SINR requirements of all nodes. To obtain the unique, Pareto optimal, and proportional fair solution, a bargaining game similar to that in (3) is formulated to obtain the solution. In this case, a node's strategy is its transmission power. The results show that the utility should be appropriately selected as a function of transmission power. The payoff function can be chosen to be $u_i(s_i) = -e^{s_i}$, where s_i, node i's strategy is the choice of transmission power.

V. Game Models of Random Channel Access

In this section, the game models for random channel access are reviewed. In particular, channel access based on ALOHA and CSMA/CA protocols are considered.

A. Channel access games in ALOHA-like protocols

In the literature, different game models, namely, noncooperative game, cooperative game, evolutionary game, and Stackelberg game models have been used for analyzing ALOHA-like channel access schemes with (and without) power control and rate adaptation. A summary of these game models is provided in Table V. The details of these models are described below.

1) Noncooperative game-theoretic approach: In [49], a noncooperative static game analysis is applied to the slotted ALOHA protocol with M selfish nodes. Actions of nodes are "To transmit" and "Not to transmit". A node has the objective to maximize its expected payoff given other nodes' transmission probabilities. The payoff is zero when a node chooses not to transmit, one when a node chooses to transmit and it is successful, and $-c_i$ when a node chooses to transmit but it is unsuccessful (here c_i is the cost of unsuccessful transmission for node i). Mixed strategy Nash equilibria are considered as the solutions which can be described as the transmission probability (i.e., the probability to perform action "To transmit" and "Not to transmit") of the nodes.

In [50], a noncooperative ALOHA game model is presented. The actions of the nodes are similar to those in [49]. However, the payoff is the utility defined as the difference between a logarithmic function of a node's SINR and the cost of transmission. Note that the transmission power is assumed to be identical for all nodes. The channel gains of other nodes are unknown, and a node's objective is to maximize its own expected utility. Note that only one node with the highest channel gain can capture

TABLE V

SUMMARY OF ALOHA-LIKE CHANNEL ACCESS GAMES

Game model	Key concept	Transmission power	Information of other nodes	Reference
Noncooperative game	Nodes choose to transmit data or not to transmit data when the payoff function of each game model is different Nodes choose their access probabilities	Fixed	N/A	[49]
			Unknown channel states	[50],[51],[52]
			Indirectly known payoff and outcome	[53]
	Nodes play both random access game and power-controlled MAC game	Not fixed	Unknown types of nodes (selfish and malicious)	[54]
			Known state information (backlogged nodes)	[55]
Incompletely-cooperative game	High and low priority nodes access the channel in both contention phase and contention-free phase	N/A	Both untruthful and truthful types reported to the access point	[57]
	Pricing mechanism used to enforce nodes to cooperate with others	Fixed	N/A	[58]
Evolutionary game	Nodes are classified into two populations, Transmit and Not to transmit	Fixed	N/A	[59]
Stackelberg game	Nodes are classified into a leader and followers. A leader node chooses its transmission strategy according to best response strategies of the followers	Fixed	N/A	[60]

the channel. Each node will gain zero payoff if it does not transmit. A node will transmit if its expected payoff is greater than zero. Bayesian Nash equilibrium is considered as a solution.

In a noncooperative ALOHA game, the Bayesian Nash equilibrium is always the threshold strategy of a channel gain. That is, a node will transmit if its channel gain is not lower than the threshold. The threshold strategy enables the system to exploit multiuser diversity by giving more chance of transmission to the node with better channel gain. To find the optimal strategy, the optimal threshold strategy has to be obtained first. In this model, only a symmetric case is considered where the cumulative distribution function (CDF) of channel gains and weights of the payoff function are identical for all nodes. The existence of a unique symmetric Bayesian Nash equilibrium is proved.

Noncooperative Bayesian static ALOHA games are also presented in [51] and [52]. Both the game models consider interference. As in [49], a fixed power is assumed in both the MAC games. The nodes do not know others' channel states (i.e., signal-to-noise ratio (SNR)). Each node decides to transmit or not to transmit the data (i.e., strategies) based on the SNR. In [51], each node will then obtain its payoff which is the difference between the utility function of SNR and the cost function if its transmission is successful. The node will pay the cost if its transmission is unsuccessful and will gain nothing if the node makes a decision not to transmit data.

Also, in [52], the payoff is the network throughput expressed as the difference between a logarithmic function of SNR and the cost of transmission power. Each node has an objective to maximize its expected payoff given a belief about other nodes' channel states (i.e., probabilities of other nodes' SNRs or channel gains) and the transmission probabilities. As in [50], only symmetric case is considered, and Bayesian Nash equilibrium is obtained as the solution of both of these games. It is found that a node will transmit if its channel gain is not lower than the SNR threshold. The existence of a unique symmetric Bayesian Nash equilibrium is proved. It is mentioned in [52] that in the static game with symmetric Bayesian Nash equilibrium, a threshold exists such that the expected payoff of "To transmit" action is equal or greater than the expected payoff of "Not to transmit" action if and only if its channel gain is greater than the equilibrium threshold and the expected payoff is equal to or greater than zero. The best-response dynamics is used to obtain a pure Bayesian Nash equilibrium strategy. The convergence time of the best-response dynamics is of the order of a polynomial of number of nodes.

In [53], nodes can observe multiple contention signals which are functions of nodes' channel access probabilities. The action of each node is to select the channel access probability. The payoff of each node is the utility which is the difference between a function of its channel access probability and the cost. The cost is defined as a function of contention measure signals (e.g., collision probability and idle time between channel access). Nash equilibrium is considered as a solution. The conditions under which the Nash equilibrium becomes efficient are established. The utility functions can be defined by using reverse engineering from existing protocol and by using forward engineering from desired operating points and based on heuristics. Since a node can observe the outcome of others' actions and payoffs indirectly, the node can use these observed information to update their distributed algorithms to converge to the Nash equilibrium.

The dynamics of the random access game is studied. Three basic dynamic algorithms (i.e., best-response based, gradient-play based, and Jacobi-play based algorithms) are presented. Also, a variant of the basic best response- based dynamic algorithm is proposed when the propagation delay is taken into account. Moreover, a dynamic algorithm under estimation error is considered. It is proved that the stochastic gradient-play algorithm converges to the equilibrium point without error.

A power-controlled MAC game and a random access game with incomplete information are presented in [54]. A node can be either selfish or malicious (i.e., type of node). In the power-controlled MAC game, the payoff of a selfish node is the expected value of the difference between a function of SINR and the energy cost. The payoff of a malicious node can be defined as two different functions depending on its opponent nodes. Two utility functions are considered, i.e., based on SINR and Shannon rate. Nash equilibrium is considered as the solution when the *types* of the nodes are known. On the other hand, Bayesian Nash equilibrium is considered as the solution when the types of the nodes are unknown. Each node maximizes its expected payoff by varying its transmission power. A Bayesian random access game, in which the nodes transmit with probabilities to maximize their payoffs, yields the same result as that of the power-controlled game. The payoff of a selfish node is the expected value from successful and unsuccessful transmissions. Also, each node dynamically updates its belief about the opponent's type using Bayes' rule.

Similar to [54], in [55], both random access game and power control game are studied. First, a random access game is presented. The payoff of node i is calculated based on the expected payoff when it transmits data, and the expected utility when it waits for transmission. A dynamic random access game is considered. At each stage of the game, nodes follow a mixed strategy (i.e., transmit or wait). Each node maximizes its payoff by choosing the transmission probability appropriately. The decision at each stage can be described as a state (i.e., the number of backlogged nodes) which is a general property of Markov games. Given the state information, the Markov perfect equilibrium at each stage of the game can be computed as the Nash Equilibrium of the mixed strategy game. Cooperation among the nodes yields a higher payoff than that of Nash equilibrium.

Next, a power control game is presented. Unlike the mixed strategy of transmitting or waiting in the random access game, power control is the mixed strategy of each node in the power control game. Each node selects its transmission probability with different power levels from a feasible set of power levels to maximize its expected payoff. This payoff depends on the probability that the captured power level at the receiver belongs to any node i.

Similar to the power control game, in a rate adaptation game, each node selects the probabilities of employing different modulation schemes (i.e., using different transmission rates) that maximize its payoff. This payoff depends on the probability that the captured rate belongs to any node i. Zero power level or zero transmission rate can be considered as the action of waiting for a transmission. To this end, a joint power control and rate adaptation game is formulated. Nodes determine their equilibrium strategies which are both the power level and transmission rate maximizing their expected payoffs. Numerical results show that power and rate control game improves the expected utilities compared to the random access game discussed in the same paper. However, the joint power and rate control game incurs a higher computational complexity.

In all the above works, it is assumed that the network has the single packet reception capability only. In contrast, in [56], a noncooperative game model was developed for optimal decentralized transmission control in a slotted ALOHA-like protocol for a finite-size random wireless network having the multipacket reception capability. The objective of each node in the network is to optimize its transmission probability such that its own utility is maximized. It is proved that if the probability of success of a node is a non-decreasing function of the corresponding SINR, there exists a threshold transmission policy which maximizes its utility. Subsequently, it is shown that there exists a Nash equilibrium at which every node adopts a threshold policy.

2) Incompletely-cooperative game-theoretic approach: In [57], a game-theoretic model of a slotted ALOHA-like MAC is presented. The model considers nodes with traffic of either high-priority (HP) or low-priority (LP). Since the nodes transmitting low priority traffic can experience an unfair channel access (i.e., HP packets have higher probability to be transmitted than that of LP packets), selfish nodes can cheat by classifying the low priority traffic as high priority traffic to gain performance improvement. To solve this problem, an access point (AP) can decide the size of contention phase (CP) and contention free phase (CFP). In the contention phase, LP queues contend for channel with probability q while HP queues contend with probability $p > q$. The access point can switch to a contention-free phase for a fraction of the time α to poll the n LP nodes. Then, the throughput that each LP node receives during CFP is α/n as shown in Fig. 4.

Average delay and throughput are used to compute the utility of HP and LP nodes, respectively. Nash equilibrium, which is a solution of this game, is any fraction of time α in which the throughput of nodes with LP traffic pretending to be the HP traffic is lower than the throughput of truthful nodes with LP traffic. Therefore, Nash equilibrium is the point where none of nodes has an incentive to lie about its traffic type. The access point can choose a value of α from an admissible range to ensure the truthful Nash equilibrium. This point can be chosen as the Nash bargaining solution from cooperative game theory.

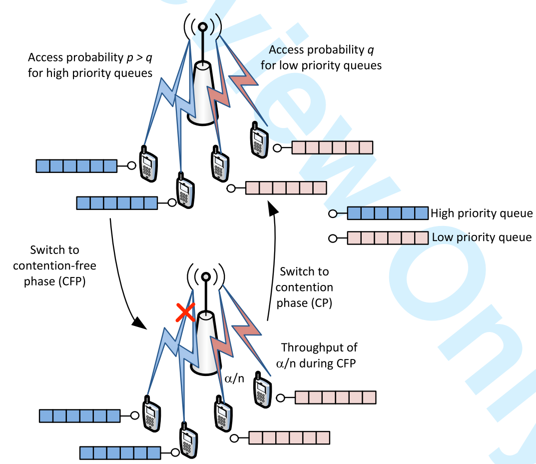

Fig. 4. High and low priority queues access the channel with different probabilities during contention phase and low priority nodes are polled equally during contention-free phase.

In [58], a pricing-based noncooperative slotted ALOHA MAC game is presented. The key contribution of this game is to motivate the nodes to cooperate with each other by using a pricing mechanism in the payoff function so that the multiuser diversity gain can be achieved. A static game is proposed in which the actions of each player $i \in \mathbb{I} = \{1, \ldots, M\}$ are "To transmit" and "Not to transmit". If a player successfully transmits the packets, the payoff is $1 - c_i - \mu_i$, where c_i is the cost of transmission and μ_i is the price charged per successful packet transmission. If the transmission is unsuccessful, the payoff is $-c_i - v_i$. If a player chooses not to transmit and it waits, the payoff is $-v_i$, where v_i is the waiting cost which is defined as $1 - c_i - \mu_i$.

In this game, each node maximizes its payoff given the medium access probabilities of all nodes. The probabilities of medium access are identical for all nodes since a fair game is considered. To maximize the expected payoff, a node will choose "To transmit" when the expected utility of "To transmit" action is not lower than that of "Not to transmit" action. Nash equilibrium, which is considered as a solution, can be found to be of threshold type. The equilibrium threshold is the cost of the corresponding action. Therefore, the transmission is successful only if there is exactly one transmitting node and transmission cost is smaller than the equilibrium threshold.

3) Evolutionary game-theoretic approach: In [59], an evolutionary game-theoretic model is formulated for ALOHA protocol. An evolutionary game is a dynamic game where players interact with other players and adapt their strategies based on payoff (fitness). The dynamics (i.e., stability) of the population adopting different strategies is studied. Also, an evolutionary stable strategy (ESS) is considered. In the evolutionary game model, if an ESS is reached, the proportions of population adopting different strategies do not change over time. In particular, the population with ESS is immune from being invaded by a population with non-ESS strategy. The effect of time delay on the dynamics of the evolutionary game model is studied. Similar to the other ALOHA games, each player has two possible strategies (i.e., "To transmit" and "Not to transmit").

For the two-player case, if a player transmits a packet, it incurs a transmission cost ($c \in (0, 1)$) irrespective of whether the transmission is successful or not. The payoffs are $1 - c$, 0, and $-c$ if the player has a successful transmission, no transmission, and collision, respectively. It is found that this game has two pure Nash equilibria (i.e., (Player I - Transmit, Player II - Not to transmit) and (Player I - Not to transmit, Player II - Transmit)) and one mixed Nash equilibrium ($1 - c$, c) where $1 - c$ and c represent proportions of individuals which transmit and do not transmit, respectively. The strategy ($1 - c$, c) can also be an ESS since this strategy is a unique symmetric Nash equilibrium.

4) Stackelberg game-theoretic approach: In [60], slotted ALOHA protocols are analyzed using game theory. The model considers throughput of the system when nodes are of self-interest and compete for bandwidth using a generalized version of slotted-ALOHA protocols. First, an analysis based on a two-state Markov model is presented when the nodes cooperate to equally share the bandwidth and maximize the system throughput. The states are "Free state" when the most recent transmission of node is successful, and "Backlogged state" when the most recent transmission is unsuccessful due to collision. The results show that the lower bound of aggregated throughput is one half and this bound is independent of the number of nodes. Next, an analysis is presented for the case when the nodes are selfish to maximize their own throughputs. Since in this case all nodes transmit with probability one, the system throughput will be zero.

Next, a Stackelberg game model is presented. A leader is any node that takes the selfish nodes (i.e., the followers) into account. The follower and leader nodes choose their best strategies (i.e., transmission probabilities in both states) by maximizing their throughputs (i.e., payoffs) subject to constraints on the *budgets* of the nodes. The budget should be higher than the cost of transmission. The followers maximize their throughputs based on the leader's strategy while the leader maximizes its own throughput according to the best response strategies of followers. Backward induction is used to find the Stackelberg equilibrium. The leader achieves a higher throughput than that of the followers when the budget is large.

B. Channel Access Games in CSMA/CA Systems

In this section, the game models formulated for analyzing CSMA/CA-based channel access are reviewed. The solution of a CSMA/CA game describes how the nodes in the network should choose their backoff windows so that the equilibrium point can be reached. Noncooperative static game-theoretic approach, noncooperative dynamic game approach, and repeated game approach can be used to model and analyze CSMA/CA systems. Since the nodes are selfish, to maximize their payoffs, the nodes may set the backoff windows to the smallest value. However, if all the nodes do so, the network throughput will be zero due to collision. To avoid this problem, incompletely-cooperative game models are used in which the nodes are enforced to cooperate in the system by using a penalizing mechanism. A summary of these approaches is provided in Table VI. The details are described below.

1) Noncooperative static game-theoretic approach: In [51], a medium access contention game model is formulated for the CSMA protocol. Similar to the slotted ALOHA protocol, the possible results from transmission attempts of each node are successful transmission, collision, and no-transmission. Transmission after k backoff slots is added to the action space of each node. The action set is $\mathbb{A} = \{1, \dots, K, K+1\}$, where $k \in \mathbb{K} = \mathbb{A} \setminus \{K+1\} = \{1, \dots, K\}$ denotes transmitting at slot k and index $K+1$ denotes the action of not-transmitting a packet. The payoff function of node i is the difference between the utility and the cost of transmission if this node selects a backoff slot number which is less than the backoff slot number of each of the other nodes. The cost of transmission incurs to node i if a collision occurs when the earliest backoff slot chosen by one (or more) of the other nodes is the same as that of node i. Node i gains nothing if it selects a backoff slot number greater than the lowest backoff slot number among the other nodes. The nodes play the game by maximizing their expected payoffs (similar to the ALOHA game models discussed in Section V-A1 before) given the type spaces (i.e., channel SNR, $\mathbf{h}$) and beliefs (i.e., probabilities of channel states of other nodes, $\mathbf{P}_{-i}(\mathbf{h}_{-i})$). A symmetric mixed strategy (in terms of the probability that the node will not transmit at the first $k \in \mathbb{K}$ slots) Bayesian Nash equilibrium is found for this single-stage (static) Bayesian game.

In [61], CSMA/CA is first modeled as a static game and then as a dynamic game (e.g., Bayesian learning game with

TABLE VI

SUMMARY OF CSMA/CA CHANNEL ACCESS GAMES

Game model	Key concept	Symmetric strategy	Method of Solution	Reference
Noncooperative game	Nodes choose to transmit or not to backoff when channel states of nodes are unknown or known to other nodes.	Yes	N/A	[51], [61]
			Best-response and gradient update algorithms	[62]
Dynamic game	K backoff slots represent K stages in a dynamic game. Nodes choose to transmit or not to transmit. The game ends when there is at least one transmission at any stage.	Yes	N/A	[51]
	Each time slot represents a stage. Their probabilities of transmission depend on the number of contending nodes.	Yes	A dynamic Bayesian-learning mechanism	[61]
	Each time slot represents a stage. Their probabilities of transmission depend on the observations of other nodes' actions	Yes	N/A	[63]
Incompletely-cooperative game	Nodes choose to transmit or to backoff. A penalizing mechanism is used to punish nodes deviating from Nash bargaining solution.	No	A round-based distributed algorithm and a coordination algorithm	[64]
	Player 1 is node i and Player 2 corresponds to all the opponents. Both the players help each other by minimizing their transmission probabilities.	No	A distributed approach used to update nodes' information	[66]
Repeated game	Nodes choose backoff slots to maximize their long-term throughput. An enforcement mechanism is used to prevent backoff attacks from misbehaving nodes.	No	CRISP cooperative mechanism	[67]

incomplete information). In the static game, the action can be "To transmit" or "Not to transmit" (i.e., wait). After node i selects its action, the utility of node i is calculated as a function of status of the packet transmission and actions of all nodes. The status can be "idle" (i.e., no transmission), "successful", or "fail" (i.e., collision). If the nodes "decide to transmit at the beginning of a given slot with probability p_i" or "stay quiet with probability $1-p_i$", for the same transmission probability by all nodes (i.e., symmetric behaviour), there is a unique solution of this static game ($s_1^* = \cdots = s_i^* = \cdots = s_M^* = p^*$) which is a symmetric mixed strategy Nash equilibrium given as follows:

$$s_i^* = 1 - \left(\frac{u^w - u^f}{u^s - u^f} \right)^{\frac{1}{M-1}} \tag{21}$$

where there are M nodes in the system and u^s, u^f, and u^w are the payoffs that a node obtains if its status is successful, failed, and idle, respectively. The dynamic game model for CSMA/CA will be described in Section V-B2.

In [62], a noncooperative game theoretic model is presented for contention control in a point-to-multipoint network (e.g., WiMAX network). Multiple subscriber stations (SSs) are connected to the a base station. A time-division duplex mode for wireless access is used for best-effort traffic. To provide multiple access services, the node has a limited number of time slots to transmit request messages (REQs). A node enters a contention resolution process when it has packets to send. A node sets its backoff counter (i.e., the number of slots that the node needs to wait before it transmits an REQ). If an REQ is successfully received and there is enough bandwidth, then the node can transmit data without collision in the scheduled time slots. The transmission is unsuccessful if a permission is not received by the node from the base station within a defined period of time, in which case, a new exponential backoff process is started. The objective here is to obtain high throughput by avoiding collision in the system. This can be achieved by gradually adjusting the contention windows of all contending nodes to the optimal values.

The game in [62] considers a saturated system (i.e., nodes always have packets to transmit). The channel access probability of node i can be found to be $p_i = 2/(CW_i + 1)$ where CW_i is a constant contention window of node i. The utility function has to be continuously differentiable, strictly concave, and with finite curvatures bounded away from zero. The utility is chosen to be a function of channel access probability which is the strategy of a node. The cost of transmission is the probability of collision ($p_i q_i(\mathbf{p})$) where $q_i(i)$ is the conditional collision probability of node i. In the game, the utility function is defined as follows:

$$\mu(p_i) = \frac{\ln(p_i) - p_i/w_i}{1/v_i - 1/w_i}. \tag{22}$$

$\mu(p_i)$ is an increasing function in the strategy space of node i (i.e., channel access probability (p_i)) where $p_i \in [v_i, w_i]$ and $0 < v_i < w_i < 1$. The payoff function is then $u(p_i) = \mu(p_i) - p_i q_i(\mathbf{p})$. Nash equilibrium (defined as $\mathbf{p}^*$) is the solution of the game. The proof of the existence of unique non-trivial Nash equilibrium (i.e., $u_i(p_i^*) = q_i(\mathbf{p}^*)$, where $q_i(i)$ is the conditional collision probability of node i), is provided. The best-response play and gradient play algorithms are presented to obtain the Nash equilibrium solution. The results show that, with this algorithm, a higher throughput is achieved with fewer transmissions than that of standard binary exponential backofff protocol.

2) Noncooperative dynamic game-theoretic approach: The single-stage CSMA Bayesian game in [51] described before is extended to a dynamic game where the static one-stage game is played repeatedly. The action of node i can be either to transmit a packet or not to transmit a packet based on node i's channel gain h_i and node i's type. K stages associated with K backoff slots are considered in this Bayesian dynamic game. At stage $k \in \{1, \ldots, K\}$, if node i successfully transmits its packet, it will obtain the payoff function, $\mu_i(h_i) - c_i(h_i)$ where μ_i is the utility function and $c_i(h_i)$ is the cost function. If node i unsuccessfully transmits its packet, it will pay $-c_i(h_i)$ as a cost of transmission; otherwise, node i gains nothing (i.e., zero payoff). If there is no transmission, the stage of the game increases from k to $k + 1$. When there is at least one transmission at any stage k, the game ends. Each node maximizes its expected payoff from stage 1 to k to obtain the perfect Bayesian equilibrium (PBE).

A symmetric PBE is considered since it is a proper operating point of a distributed protocol for the following reasons. First, it might not be possible to distinguish among nodes in the random access network. Second, asymmetric PBE is not sustainable since it causes unfairness problem by assigning unequal shares of channel to the nodes. Third, it is much simpler to operate a network with a single strategy in a symmetric equilibrium for all nodes than to operate a network with different strategies for different nodes. The symmetric PBE is shown to be a threshold strategy. That is, any node i decides to transmit at stage k when its SNR is greater than SNR threshold $h_t^k h$ (i.e., $h_i > h_t^k h$). The numerical results show that the proposed protocols provide better robustness and higher multi-user diversity gain than those of conventional random access protocols.

The static game is extended to a dynamic Bayesian-learning game with the unknown number of contending nodes in [61] (i.e., the static game is played repeatedly). There are maximum of M nodes in the system. These nodes compete for transmission at the beginning of a time slot. Fairness requirement is considered. In order to maximize the payoffs of the nodes, only symmetric strategy with $s_1^* = \cdots = s_i^* = \cdots = s_M^* = p^*$, which is the probability of transmission, is considered. Each time slots corresponds to a stage in this dynamic game. Since the number of contending nodes is unknown, each node needs to observe the feedbacks from its previous play. Then, the node can build its belief about the network using Bayes' rule.

It is assumed that all nodes can keep track of their historical information perfectly. Three counters (i.e., the total number of passed time slots, the total number of successfully transmitted data packets, and the number of times that ACK control-frame is not received in a pre-defined time space after transmitting the data packet) are used to compute the belief. The current packet transmission probability and the frame collision probability of each node can be computed by these three counters under the assumption that all nodes always have packets to transmit. Each node has to listen to the channel to receive any possible packet from its neighbouring nodes when it is idle. After that, each node can obtain the posterior belief of the number of concurrently contending nodes (n) for the channel by using both the transmission and collision probabilities (i.e., p and q, respectively) as follows:

$$n = f(p, q) = 1 + \frac{\log(1-q)}{\log(1-p)}. \tag{23}$$

It is found that the equilibrium optimal solution of this game depends on the number of contending nodes n. The transmission probability can be varied according to the following equation in which only contention parameter CW_{min} (i.e., minimum contention window) is considered:

$$p = \frac{2(1-2q)}{(1-2q)(CW_{min}+1) + q.CW_{min}.(1-(2q)^n)} \tag{24}$$

where $CW_{min} = \min([n \times rand(7,8)], CW_{max})$, $rand(x, y)$ returns a random value between x and y, and n is the number of concurrently contending nodes. The game state n can be then updated using (23) after a node updates its beliefs. Simulation results show that the performance of the dynamic CSMA game-based MAC is superior to the IEEE 802.11 DCF MAC in terms of throughput, delay, and packet-loss rate.

Another dynamic game model for CSMA/CA is proposed in [63], where the probabilities of transmission are the strategies of the nodes. Each node estimates its conditional collision probability and adjusts the persistence probability. The payoff of each node is the difference between the utility when the node accesses the channel with probability p_i and the cost (i.e., probability of collision). For a network with homogeneous nodes, the game model has a unique nontrivial Nash equilibrium which is a symmetric equilibrium. This guarantees fair sharing of wireless channel among the same class of nodes. Next, the dynamics of the game is studied. Although one node can observe the outcome of other nodes, it does not have complete knowledge of actions and payoffs of other nodes. Every node adjusts its current channel access probability gradually in the gradient direction based on the observations of other nodes' actions. Then, the Nash equilibrium can be reached.

Based on the dynamics of this random access game, a new MAC protocol based on CSMA/CA is proposed. Instead of executing exponential backoff upon collisions, each node estimates its collision probability and contention window according to gradient play. Each node can estimate its conditional collision probability by observing the average number of consecutive idle slots. Therefore, the size of contention window can be adjusted accordingly. Throughput and short-term fairness of the proposed MAC protocol are better than those of the IEEE 802.11 DCF protocol. Service differentiation is also considered. When there is more than one class of nodes, the throughput ratio can converge to a constant when the total number of nodes increases.

3) Incompletely-cooperative game-theoretic approach: In [64], a CSMA/CA-based MAC game model is presented for dynamic spectrum access in a cognitive radio network. This game model can be divided into two sub-games. The first sub-game is a channel allocation game in which the nodes compete to allocate radio interfaces to the channels. The second sub-game is a multiple access game among the nodes contending to transmit packets in the same channel. The available frequency band is divided into K channels of the same bandwidth. Each node is equipped with l radio interfaces for $l < K$. Each node can hear other nodes' transmissions if the same channel is used. Each node determines the number of interfaces to be used in each channel. This is the action of nodes in the first sub-game of channel allocation. Each node maximizes its utility function which is the sum of throughputs achieved by the node in all allocated channels. Each node can observe other nodes' information perfectly. The solution of the channel allocation game is the Nash equilibrium if the difference between the number of interfaces in any channel x and that in any other channel y is lower than or equal to 1. Also, the number of interfaces allocated to any channel x by node i is lower than or equal to 1 for any channel y. It is found that if the rate function of each channel is independent of the number of interfaces in any channel, then any Nash equilibrium of channel allocation is Pareto optimal.

The existence of Nash equilibrium is shown and its efficiency (i.e., price of anarchy) is studied. It is found that the price of anarchy is close to one (i.e., Nash equilibrium yields a payoff close to that of the socially optimal solution).

Next, the second sub-game for CSMA/CA channel contention is formulated. This sub-game aims not only to optimize the network performance, but also to provide incentives to the nodes to behave optimally. The actions of the nodes are "To transmit", "Not to transmit", and "To backoff" in which a contention window value between one and the maximum value is chosen by a node. Node i selects the value of contention window on each channel c to maximize its throughput (i.e., payoff). The static CSMA/CA game shows that the Nash equilibrium (i.e., contention window is chosen to be one) is inefficient and unfair.

A desirable solution for the CSMA/CA game should have three properties: uniqueness, per-radio fairness, and Pareto optimality. Using the Nash bargaining framework from the cooperative game theory, these three properties can be achieved. However, in the noncooperative regime, the Nash bargaining solution is not a Nash equilibrium and might not be stable. Therefore, a penalizing mechanism is introduced by which the node deviating from Nash bargaining solution will be punished. A jamming mechanism is presented to penalize the deviating node. The deviating node is selectively jammed for a short duration by the other nodes using the channel when the deviating node is detected doing selfishly for its transmission. Using the penalty function and the jamming mechanism, the game can reach a Nash equilibrium unilateral deviation from which is not profitable. A distributed algorithm is proposed to obtain the Pareto-optimal Nash equilibria. The algorithm can converge to the equilibrium point even in case of imperfect information. The algorithm is based on a round-based distributed algorithm [65]. Also, a coordination algorithm is proposed for CSMA/CA in which one node acts as a coordinator for the observed channel by inflicting penalties to the other nodes which receive a higher throughput.

		Player 2 (All opponents)		
		Backoff	Successful transmission	Unsuccessful transmission
Player 1 (node *i*)	Backoff	(μ_b^1, μ_b^2)	(μ_b^1, μ_s^2)	(μ_b^1, μ_f^2)
	Transmission	(μ_s^1, μ_b^2)	(μ_f^1, μ_f^2)	

Fig. 5. Strategies of two players when Player 1 is node i and Player 2 refers to all opponent nodes [66].

In [66], an incompletely cooperative game model is presented for wireless mesh networks. The routers and clients communicate wirelessly with each other in a mesh architecture. CSMA/CA is used as a channel access mechanism. Since a packet can be retransmitted only for a certain number of times, the game model can be formulated as a finite repeated game. The number of opponents can be estimated by using conditional collision probability and transmission probability. These probabilities are computed by the node using two local counters (the total number of successfully transmitted data frames and the total number of transmitted data frames which are unsuccessful). However, these estimations are accurate only under saturated conditions (i.e., nodes always have packets to transmit).

A virtual CSMA/CA mechanism, V-CSMA/CA is proposed. V-CSMA/CA follows the CSMA/CA scheme but it handles virtual frames. V-CSMA/CA will send a virtual frame and then the probability of collision is estimated. If the channel is idle, the node will observe that the virtual frame is successfully transmitted. A collision of virtual frame will be detected whenever any other node chooses the same time slot for transmission of their real data frame. If the node has no packet to transmit, the game state is estimated by using V-CSMA/CA. If the node has packets to transmit, the game state is estimated by using CSMA/CA.

In the analysis of the game, a player is not always fixed. That is, Player 1 stands for node i and Player 2 stands for all other opponent nodes. The actions of Player 1 are "Transmission" and "Backoff". The actions of Player 2 are "Successful Transmission" (i.e., Player 1 selects "Backoff" and none of the nodes in the group of Player 2 selects "Transmission"), "Unsuccessful Transmission" (i.e., Player 1 selects "Backoff" but a node in the group of Player 2 selects "Transmission"), or "Backoff" as shown in Fig. 5. μ_b^i, μ_f^i, and μ_s^i are utility obtained when Player i chooses to backoff, to transmit and transmission is successful, and to transmit but transmission fails, respectively. The optimal strategy of each player (s_i^*) can be found by minimizing its payoff by varying the transmission probability p_i. It can be considered as a mixed strategy solution. Then, the cooperation among the nodes considered. In a two-node scenario, one node adjusts its transmission probability to help the other node to achieve the optimal payoff (i.e., $p_1^* = \arg\min_{p_1} u_1(p_2, p_1)$ and $p_2^* = \arg\min_{p_2} u_2(p_1, p_2)$, where $u_1(\cdot)$ and $u_2(\cdot)$ are payoff functions of Players 1 and 2 which are based on each other's utility of transmission, respectively.

The transmission probabilities can be changed by tuning the MAC contention parameters as in [61]. After estimating the game state, the mesh router broadcasts its estimated information to all nodes. Since in a dynamic network frequent information updates are needed, this may result in large overhead. To reduce the overhead, a distributed approach is used by each node to detect the channel, estimate the game state, and adjust the contention parameters. Moreover, the estimation is performed after a packet is transmitted or a packet is discarded (rather than in every time slot). Also, the contention parameter is adjusted accordingly. The simulation results show that the incompletely cooperative game can improve throughput and decrease delay, jitter, and packet loss rate. The fairness of this game is comparable to that of the IEEE 802.11 DCF protocol.

4) Incompletely-cooperative repeated game-theoretic approach: In [67], a game-theoretic study of CSMA/CA under a backoff attack is presented. An enforcement mechanism is introduced for the misbehaving nodes in the network. Although this enforcement mechanism is similar to that in [64], here it is used in the context of a mobile ad hoc network and the game formulation is for a repeated game in which a long-term utility is to be maximized. First, a noncooperative game is formulated for a finite number of nodes. Each node chooses an action which is a backoff configuration from a feasible set. The payoff function is defined to be the bandwidth share function depending on the backoff configuration profile ($\mathbf{s} = (s_1, \ldots, s_i, \ldots, s_M)$). Nash equilibrium is the solution of this one-shot noncooperative game which might be unfair or inefficient. Therefore, to obtain a better solution, a repeated game is proposed in which a node takes into account the effect of its current action on the future actions of other nodes. The number of stages is finite and should be large enough to approach the steady state values. Nodes can switch between standard or non-standard backoff configuration (i.e., fair or more-than-fair bandwidth share, respectively) to maximize their own long-term payoffs.

To prevent the backoff attack and to obtain a fair Pareto optimal and sub-game perfect Nash equilibrium, a strategy profile called cooperation via randomized inclination to selfish/greedy play (CRISP) is introduced. This optimal solution is a probability distribution over the selected backoff configuration at stage k (s_i^k). An invader node deviating from CRISP will experience lower bandwidth than that of nodes playing CRISP.

VI. Summary of Game Models and Open Research Issues

A. Summary of Game Models

Table VII summarizes the game models formulated for the key multiple access mechanisms. In the channel access games for TDMA, nodes compete with each other to obtain time slots for their transmissions. Time slot allocation among the nodes is performed by using various game models. In the auction game models, the nodes bid for time slots and they have to pay to the base stations for the allocated time slots. Game models can be formulated in which the nodes are able to choose transmission power in their allocated time slots. To enforce cooperation among the nodes, a punishment and truth-telling mechanism can be used.

In the channel access games for FDMA, most of the models consider how nodes (with single or multiple radio interfaces) choose channels for transmission. In these game formulations, the number of radios, transmit rate, and power rate assigned to each channel correspond to nodes' actions. In the channel access games for CDMA, power control is the key objective of all the proposed games. Both cooperative and noncooperative games can be formulated. Nodes select their transmission powers to meet their requirements in terms of SINR and transmission cost.

In most of the ALOHA-like game models, the nodes can choose either "To transmit" or "Not to transmit" as their possible action and the transmission powers of the nodes are assumed to be fixed. Then, the games have mixed strategy solutions. Some of the games can be shown to have solutions which are threshold strategies. In some of the CSMA/CA game models, the actions are "To transmit" and "To wait for k back off time slots". The solutions of these game models are mixed strategies

TABLE VII

SUMMARY OF CHANNEL ACCESS GAMES

Access Scheme	Summary
TDMA	In TDMA access games nodes compete for time slots to achieve their objectives and meet QoS requirements. Noncooperative static game, auction game, dynamic game, and repeated game models can be applied for TDMA.
FDMA	In FDMA, nodes compete for the available channels in the network (e.g., through an auction mechanism). The solution in terms of equilibrium can be achieved for the complete and incomplete information cases. Noncooperative static game, auction game, and cooperative game models can be used for FDMA.
CDMA	In a CDMA system, each node is assigned with a different code to allow multiple users to be multiplexed over the same channel at the same time. Power control is crucial for CDMA to ensure that the received signal can be decoded correctly. In a CDMA system with self-interested nodes, the transmission power control can be modeled as complete and incomplete information noncooperative games. Also, cooperative game model for group-rational nodes can be used to achieve a Pareto optimal power control strategy.
ALOHA	Noncooperative game, cooperative game, evolutionary game, and Stackelberg game models can be used for ALOHA-like channel access. For the majority of the models, the solution is a threshold strategy. Along with channel access, power control and rate adaptation are also considered in the models.
CSMA/CA	In CSMA/CA games, the nodes in the network choose their backoff windows so that the equilibrium point can be achieved. Noncooperative static game, noncooperative dynamic game, and repeated game models can be applied for CSMA/CA. Since the nodes can be selfish (i.e., to maximize their payoffs, they may set the backoff windows to be the smallest value), a penalizing mechanism is required for the misbehaving nodes.

(i.e., the transmitting probability of nodes at the first k time slots). In some CSMA/CA-like MAC game models, the action set of nodes is defined as transmission probabilities. In addition, most of the CSMA/CA-like MAC game models consider only the symmetric strategy case by assuming that all nodes are identical and throughput maximization is the key objective. Since in random access schemes, nodes access the channel(s) in a distributed manner, some nodes may misbehave. A penalizing mechanisms is required to address this problem. A summary of game models for contention-free channel access approaches is shown in Table VIII and a summary of game models for random channel access approaches is shown in Table IX.

In the next section, we present several open research issues on game theoretic modeling of multiple access in wireless networks.

B. Open Research Issues

Based on the summary of the game models presented in the previous section, several open research issues on the application of game theoretic models for design, analysis, and optimization of multiple access schemes for wireless networks can be identified as follows:

TABLE VIII

GAME THEORY MODELS FOR CONTENTION-FREE CHANNEL ACCESS

Issues	Game type	Player	Strategy	Payoff	Solution
Time slot competition [23]	Noncooperative game	Mobile nodes	Fraction of time in the slot	Time slot usage	Nash equilibrium
Time slot competition [25]	Auction game	Mobile nodes and a base station	Bid value between 0 and 1	Amount of data transmitted	Nash equilibrium
Time slot competition [26]	Auction game	Mobile nodes and a base station	Monetary units	Amount of data transmitted	Nash equilibrium
Time slot competition and transmission rate control [27]	Markov game	Secondary nodes in TDMA cognitive radio	Transmission rate	Discounted transmission cost	Nash equilibrium
Time slot competition and transmission rate control [28]	Markov game	Secondary nodes in TDMA cognitive radio	Transmission rate	Discounted transmission cost minus a function of transmission delay	Correlated equilibrium
Time slot allocation [29]	Repeated game	Mobile nodes	Power allocated to each time slot	Long-term throughput	Nash equilibrium
Time slot allocation [29]	Repeated game with incomplete information	Mobile nodes	Channel gain to each time slot	Transmission rate plus transfer function	Nash equilibrium
Channel allocation [30]	Noncooperative game	Mobile nodes with multiple radios	The number of radios assigned to each channel	Throughput minus cost	Strongly dominant - strategy equilibrium
Sub-channel allocation [32]	Noncooperative game	Mobile nodes	Rate assigned to each sub-channel	Transmission power minimization	Nash equilibrium
Channel allocation [33]	Noncooperative game	Mobile nodes with multiple radios	The number of radio assigned to each channel	Achieve bit rate	Nash equilibrium
Sub-channel and power allocations [34]	Noncooperative game	Base stations	Transmission power and sub-channel assigned to mobile nodes	Data rate	Nash equilibrium
Channel allocation [35]	Noncooperative game	Secondary nodes	Channel selection	Function of SINR	Nah equilibrium
Channel allocation [35]	Stackelberg game	Secondary nodes	Channel selection	Function of SINR and cost of switching channel	Nash equilibrium
Transmission power allocation [36]	Auction game	Mobile nodes and a base station	Power control variable and bid value	Shannon capacity	Nash equilibrium
Cooperative group formation [38] in multi-channel network	Coalitional game	Secondary base stations	Coalition's member selection	Utility from learning new channels minus cost of cooperation	Nash equilibrium (Nash-stable formation)
Sub-channel assignment and [40] power allocation	Coalitional game	Mobile nodes	Transmission power assigned to each channel	Function of Shannon-capacity	Nash equilibrium
Power control in CDMA [41]	Noncooperative game	Mobile nodes	Transmission power selection	Fraction of throughput to transmission power	Nash equilibrium
Power control in CDMA [42]	Bayesian game	Mobile nodes	Transmission power selection	Difference between throughput and power consumption	Bayesian Nash equilibrium
Power control in CDMA [43]	Noncooperative game	Mobile nodes	Transmission power selection	Difference between throughput (bits/second) and cost of transmission power	Nash equilibrium
Joint rate and power control in CDMA [44],[46]	Noncooperative game	Mobile nodes	Transmission power and rate selections	Utility in bits/J	Nash equilibrium
Power control in CDMA [47]	Noncooperative game	Mobile nodes	Transmission power selection	cost a function of power and SIR	Nash equilibrium
Optimal power allocation [48]	Bargaining game	Mobile nodes	Transmission power selection	Any appropriate function	Nash bargaining solution

TABLE IX

GAME MODELS FOR RANDOM CHANNEL ACCESS

Issues	Game type	Player	Strategy	Payoff	Solution
Slotted ALOHA channel access [49]	Noncooperative game	Mobile nodes	"To transmit" and "Not to transmit"	Reward and cost of transmission	Mixed strategy Nash equilibrium
Slotted ALOHA channel access [50] with unknown channel gains	Bayesian game	Mobile nodes	"To transmit" and "Not to transmit"	Function of SINR minus cost of transmission	Bayesian Nash equilibrium (Strategy threshold)
Slotted ALOHA channel access [51] with unknown SNR	Bayesian game	Mobile nodes	"To transmit" and "Not to transmit"	Function of SNR minus cost function of SNR	Bayesian Nash equilibrium (Strategy threshold)
CSMA/CA channel access [51]	Noncooperative game	Mobile nodes	Transmission and Backoff	Reward and cost of transmission	Mixed strategy Nash equilibrium
CSMA/CA channel access [51]	Dynamic game with incomplete information	Mobile nodes	"To transmit" and "Not to transmit" function of SNR	Utility and cost- equilibrium	Perfect Bayesian
Interference-aware MAC [52] with unknown channel gains	Bayesian game	Mobile nodes	"To transmit" and "Not to transmit"	Function of SNR minus cost of transmission power	Bayesian Nash equilibrium (Strategy threshold)
Multiple channel access[53]	Noncooperative game	Mobile nodes	Channel access probabilities	Function of access probability minus function of contention signals	Nash equilibrium
Power control / random access [54]	static game/ Bayesian game	Mobile nodes	Transmission power/ "To transmit" and "Not to transmit"	SINR minus energy cost/ Reward and cost of transmission	Nash/ Bayesian Nash equilibrium (Strategy threshold)
Power control, joint power and rate control /random access [55]	Noncooperative static/ Markov game	Mobile nodes	Transmission power and rate / "To transmit" and "Not to transmit"	Function of captured packets/ power level/ rate probabilities/	Mixed strategy Nash equilibrium
ALOHA-like MAC [57] with prioritized nodes	Incompletely-cooperative game	Access point	Fraction of time	Delay (HP nodes) and throughput (LP nodes)	Nash equilibrium and Nash Bargaining Solution
Slotted ALOHA channel access [58]	Incompletely-cooperative game	Mobile nodes	"To transmit" and "Not to transmit"	Transmission cost, waiting cost and price	Nash equilibrium (Strategy threshold)
Slotted ALOHA channel access [59]	Evolutionary game	Subpopulations of mobile nodes using same strategies	"To transmit" and "Not to transmit"	Cost of transmission	Evolutionary stable strategy
Slotted ALOHA channel access [60]	Stackelberg game	Mobile nodes	Transmitting probability	Throughput	Stackelberg equilibrium
New CSMA/CA-like MAC [61]	Noncooperative game	Mobile nodes	"To transmit" and "Not to transmit"	Not specified	Mixed strategy Nash equilibrium
New CSMA/CA-like MAC [61]	Dynamic game	Mobile nodes	"To transmit" and "Not to transmit"	Not specified	Mixed strategy Nash equilibrium
Contention control in WiMAX [62]	Noncooperative game	Mobile nodes	Transmitting probability	Function of channel access probability	Non-trivial Nash equilibrium
New CSMA/CA-like MAC [63]	Dynamic game	Mobile nodes	Transmitting probability	Function of transmission probability minus collision probability	Mixed strategy Nash equilibrium
CSMA/CA channel access[64]	Incompletely-noncooperative game	Mobile nodes	Transmission and Backoff	Throughput	Pareto-optimal Nash equilibrium
CSMA/CA channel access [66]	Incompletely-noncooperative	Mobile nodes	Transmission and Backoff	Not specified	Mixed strategy Nash equilibrium
CSMA/CA under attack [67]	Repeated game	Mobile nodes	Transmission and Backoff	Bandwidht share	Perato optmal and subgame-perfect Nash equilibrium

- *Investigation of different equilibrium concepts*: Many works in channel access games only study Nash equilibrium as the solution concept. However, Nash equilibrium does not always provide the best network performance. Therefore, other equilibrium concepts need to be investigated. For example, Nash bargaining solution, which is Pareto optimal, can be considered for efficiency and fairness reasons. Another solution is correlated equilibrium which is a more general equilibrium concept than the Nash equilibrium and also incurs less computational complexity. It can be computed in polynomial time for essentially all kinds of multi-player games.
- *Utility and cost function design*: In the application of game theory to multiple channel access, utility and cost indicate, respectively, the preference of players to be maximized and to be minimized for channel access. There are many different functions used to represent payoff of players in channel access games. Comparisons among the utility functions in terms

of performance and effectiveness may be required. Also, the utility functions should consider system parameters such as the priorities of packets, amount of battery power available, and application-layer QoS parameters. To obtain suitable utility functions that can converge to desirable equilibria, reverse engineering from existing protocols, desired operating points, or forward engineering from heuristics [68] can be used.

- *Cooperation enforcement mechanism*: In random channel access games, many works propose cooperation enforcement mechanisms in noncooperative scenarios. Penalizing and pricing mechanisms are introduced. However, the complexity and implementation issues of these mechanisms (e.g., jamming and detection mechanisms) need to be investigated while developing practical protocols. In this case, a pricing mechanism may be preferred over a penalizing mechanism since pricing schemes are easier to be implemented by service providers.
- *Uncertainty in wireless and mobile networks and accuracy of available information*: Some game models are formulated as dynamic or repeated games in order to analyze the outcomes in long-run periods. Most games assume that the number of nodes in the network is constant; however, in realistic scenarios, the number of nodes changes over time (i.e., nodes leave or join the network). In random channel access games, the number of nodes can be estimated by using probabilities of packet transmission and collision. It might be acceptable if the time duration of one stage of the game is short or the game is not played infinitely. However, it is not completely true for all games. Moreover, most games assume that the nodes completely know other nodes' information. The assumption may not always hold in a mobile wireless network. Then, unknown information has to be estimated based on some available knowledge of mobiles and their belief models (i.e., probability distribution). Currently, there are few works using game-theoretic approaches with incomplete information. Bayesian game and Bayesian-learning mechanism are useful tools to study the multiple access problem under incomplete information. More works in this area are required to model and analyze distributed multiple access methods in large-scale wireless networks.
- *Cost of information*: The Bayesian Nash equilibrium for incomplete information game may be inefficient due to the lack of complete information. Nodes can implement the information gathering mechanism so that a better decision can be made. However, the cost of information collection needs to be considered and a cost-benefit analysis needs to be performed.
- *Develop defense mechanisms against multiple access attack*: Defending attacks from untrusted nodes is an important research issue in wireless networks. Malicious nodes prevent other nodes from accessing the network (i.e., denial-of-service (DoS) attack). For example, jamming attack is a form of DoS attack. There are some channel access games which take security issues into consideration. However, most of these game-theoretic models analyze the interactions between pairs of jammers and communicating nodes or between pairs of jammers and detecting nodes when an intrusion detection

system (IDS) is deployed [69]-[70]. A few researches such as those in [71]-[73] formulate games between jammers and communicating nodes in order to analyze equilibrium points as defense strategies against jamming attacks. More researches in this area are required. For example, we can formulate a noncooperative game with incomplete information when types of nodes such as selfish, malicious, or defending (i.e., when IDS is deployed) are incompletely known to other nodes.

- *Multiple access in heterogeneous wireless networks*: Channel allocation and multiple access problem in a heterogeneous wireless access network can be modeled by using game theory. In a heterogeneous network the service providers for the different wireless access networks as well as the mobile users (who are able to access the different networks using multiple radio interfaces) may cooperate or compete with each other. Game theoretic modeling and analysis of the interactions among the mobile nodes and service providers is an interesting research topic. Again, in a heterogeneous network where a bi-level hierarchy exists (e.g., in a cellular network where macrocells are underlaid with femtocells), transmission power and rate control problem (e.g., by the macro base stations and the femto access points) for multiple access can be modeled by using game theory, and optimal multiple access method can be designed.
- *Develop application-centric game models for multiple access*: Traditional multiple access schemes may not be efficient in some specific wireless access scenarios such as in vehicular networks and wireless sensor networks. There are two steps in designing MAC protocols for a specific application [74]. First, the application requirements and the resource constraints are specified. Next, a protocol that satisfies all these constraints is designed. For example, in vehicular networks, high mobility that causes the topology of the network to vary rapidly is one of the application specifications, and transmission delay (i.e., emergency messaging delay) is an application requirement. Limited bandwidth due to high vehicle mobility and vehicle density is one of the resource constraints. These specifications and requirements need to be considered when designing a multiple access method for vehicular networks. For a game theoretic multiple access scheme, the utility functions for the players should take the related parameters into account. Due to the applications' specific requirements and specifications, developing game models for application-centric multiple access is more challenging.

VII. Conclusion

Game theory has been widely used to model and analyze the noncooperative and cooperative behaviours of mobile nodes in the context of multiple access in wireless networks. The game models are useful for designing distributed channel access mechanisms in wireless networks to achieve stable and efficient solutions. This article has presented a comprehensive survey of the game models developed for multiple access in wireless networks. These game models have been categorized based on the types of protocols (e.g., contention-free or contention-based) and types of games (e.g., complete and incomplete information, and static and dynamic games). The major findings from these game models have been discussed. Unavailability of complete information, misbehaviour of nodes, consideration of system (i.e., implementation) aspects give rise to major challenges in designing game theoretic design of multiple access schemes in wireless networks. From these perspectives, several open research directions have been outlined.

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