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USING GAME THEORY TO ANALYZE WIRELESS AD HOC NETWORKS

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ABSTRACT

The application of mathematical analysis to the study of wireless ad hoc networks has met with limited success due to the complexity of mobility and traffic models, the dynamic topology, and the unpredictability of link quality that characterize such networks. The ability to model individual, independent decision makers whose actions potentially affect all other decision makers renders game theory particularly attractive to analyze the performance of ad hoc networks. In this article we describe how various interactions in wireless ad hoc networks can be modeled as a game. This allows the analysis of existing protocols and resource management schemes, as well as the design of equilibrium-inducing mechanisms that provide incentives for individual users to behave in socially-constructive ways. We survey the recent literature on game theoretic analysis of ad hoc networks, highlighting its applicability to power control and waveform adaptation, medium access control, routing, and node participation, among others.

A wireless ad hoc network is characterized by a distributed, dynamic, self-organizing architecture. Each node in the network is capable of independently adapting its operation based on the current environment according to predetermined algorithms and protocols. Analytical models to evaluate the performance of ad hoc networks have been scarce due to the distributed and dynamic nature of such networks. Game theory offers a suite of tools that may be used effectively in modeling the interaction among independent nodes in an ad hoc network. In this article we describe how such games can be set up and discuss recent advances in this area.

BASICS OF GAME THEORY

Game theory is a field of applied mathematics that describes and analyzes interactive decision situations. It provides analytical tools to predict the outcome of complex interactions among rational entities, where rationality demands strict adherence to a strategy based on perceived or measured results. The main areas of application of game theory are economics, political science, biology, and sociology. Since the early 1990s, engineering and computer science have been added to this list.

We limit our discussion to non-cooperative models that address the interaction among individual rational decision makers. Such models are called "games" and the rational decision makers are referred to as "players." In the most straightforward approach, players select a single action from a set of feasible actions. Interaction between the players is represented by the influence that each player has on the resulting outcome after all players have selected their actions. Each player evaluates the resulting outcome through a payoff or "utility" function representing her objectives. There are two ways of representing different components (players, actions, and payoffs) of a game: normal or strategic form, and extensive form. Here we will focus on the normal form representation. Formally, a normal form of a game G is given by $G = \langle N, A, \{u_i\}\rangle$ where $N = \{1, 2, \ldots, n\}$ is the set of players (decision makers), A_i is the action set for player i, $A = A_1 \times A_2 \times \cdots \times A_n$ is the Cartesian product of the sets of actions available to each player, and $\{u_i\} = \{u_1, \ldots, u_n\}$ is the set of utility functions that each player i wishes to maximize, where $u_i: A \rightarrow \mathbf{R}$. For every player i, the utility function is a function of the action chosen by player i, a_i, and the actions chosen by all the players in the game other than player i, denoted as $\mathbf{a}_{-i}$. Together, a_i and $\mathbf{a}_{-i}$ make up the action tuple $\mathbf{a}$. An action tuple is a unique choice of actions by each player. From this model, steady-state conditions known as *Nash equilibria* can be identified. Before describing the Nash equilibrium we

User 3 = Share		
User 1 \ User 2	Share	Not share
Share	0.5, 0.5, 0.5	–0.5, 2, –0.5
Not share	2, –0.5, –0.5	1, 1, –1.5
User 3 = Not share		
User 1 \ User 2	Share	Not share
Share	–0.5, –0.5, 2	–1.5, 1, 1
Not share	1, –1.5, 1	0, 0, 0

Table 1. *A payoff matrix for a three-player peer-to-peer file sharing game.*

define the best response of a player as an action that maximizes her utility function for a given action tuple of the other players. Mathematically, $\bar{a}$ is a best response by player i to $\mathbf{a}_{-i}$ if

$$\bar{a} \in \{\text{argmax } u_i(a_i, \mathbf{a}_{-i})\}$$

A Nash equilibrium (NE) is an action tuple that corresponds to the mutual best response: for each player i, the action selected is a best response to the actions of all others. Equivalently, a NE is an action tuple where no individual player can benefit from unilateral deviation. Formally, the action tuple $\mathbf{a}^* = (a_1^*, a_2^*, a_3^*, \dots a_n^*)$ is a NE if $u_i(a_i^*, \mathbf{a}_{-i}^*) \geq u_i(a_i^*, \mathbf{a}_{-i}^*)$for $\forall a_i \in A_i$ and for $\forall i \in N$. The action tuples corresponding to the Nash equilibria are a consistent prediction of the outcome of the game, in the sense that if all players predict that a Nash equilibrium will occur then no player has any incentive to choose a different strategy. There are issues with using the Nash equilibrium as a prediction of likely outcomes (for instance, what happens when multiple such equilibria exist?). There are also refinements to the concept of Nash equilibrium tailored to certain classes of games. A detailed discussion of these is outside the scope of this article.

There is no guarantee that a Nash equilibrium, when one exists, will correspond to an efficient or desirable outcome for a game (indeed, sometimes the opposite is true). Pareto optimality is often used as a measure of the efficiency of an outcome. An outcome is Pareto optimal if there is no other outcome that makes every player at least as well off while making at least one player better off. Mathematically, we can say that an action tuple $\mathbf{a} = (a_1, a_2, a_3, \dots, a_n)$ is Pareto-optimal if and only if there exists no other action tuple $\mathbf{b} = (b_1, b_2, b_3, \dots, b_n)$ such that $u_i(\mathbf{b}) \geq u_i(\mathbf{a})$ for $\forall i \in N$, and for some $k \in N$, $u_k(\mathbf{b}) > u_k(\mathbf{a})$.

To illustrate these basic concepts, consider a peer-to-peer file sharing network modeled as a normal form game. The players of the game are individual users who experience a trade-off in sharing their files with others. For simplicity consider a network of three users. Each user has the option of either sharing their files or not sharing. Thus, the action set of each player is {Share, Not share}. The payoff to each user is given by the sum of the benefits she experiences when other users share their files, and the cost she incurs by sharing her own files. We assume the users to be limited in resources. We assign the payoffs such that each user benefits by 1 unit for each other user that shares files and incurs a cost of 1.5 units in sharing her own files. The payoff matrix can be represented as in Table 1. In the payoff matrix, the payoff for user 1 is listed first, the payoff for user 2 is listed second, and the payoff for user 3 is listed third. Rather than attempting to represent the three-dimensional action space as a single object, we have presented the action space in two two-dimensional slices.

From the payoffs we observe that the best response of each user irrespective of other users' actions is to not share. The unique NE is the action tuple (Not share, Not share, Not share). Also, it is evident that no user accrues any benefit by unilaterally deviating and sharing her files. One should note that the Nash equilibrium is *not* Pareto optimal in this case. The outcome (Share, Share, Share) would make all three players better off than the NE action tuple. Those familiar with game theory will recognize this formulation as a three-player version to the Prisoners' Dilemma game [1].

Why Game Theory?

For over a decade game theory has been used as a tool to study different aspects of computer and telecommunication networks, primarily as applied to problems in traditional wired networks. In the past three to four years there has been renewed interest in developing networking games, this time to analyze the performance of wireless ad hoc networks. Since the game theoretic models developed for ad hoc networks focus on distributed systems, results and conclusions generalize well as the number of players (nodes) is increased. It is also of interest to investigate how selfish behavior by individual nodes may affect the performance of the network as a whole.

Consider, as an example, an ad hoc network implementing a pure slotted Aloha protocol. Nodes are constantly entering and leaving the network, so the number of nodes in the network, n, is not generally known. As such, the optimal retransmit probability, $p = 1/n$, cannot be globally set to maximize throughput. Each node must then adapt its retransmit probability to current network conditions to maximize its throughput, perhaps guided by channel observations and channel occupancy estimations. In this way we can devise an algorithm for a node to attempt to predict the response of the other nodes in the network without precise knowledge of the total number of nodes. An important question is whether the algorithm that governs this dynamic adaptation has a desirable steady-state. Even if it does, how can we be certain that the network behavior will converge to this steady-state? Will small perturbations to the system dramatically alter behavior? Will increasing the number of nodes past some point result in undesirable drift? These are the type of questions that game theory has been utilized to answer, not just with respect to Medium Access Control (MAC) protocols, but also distributed adaptations at the physical, network, and transport layers.

As seen from Table 1, selfish behavior may lead to a NE that is socially undesirable. Therefore, from a system designer's perspective it is imperative to make the network robust to selfish behavior, perhaps by providing mechanisms that render selfish behavior unprofitable to the nodes that employ it. Game theory can be used to better understand the expected behavior of nodes and engineer ways to induce a socially desirable equilibrium.

Our main contributions in the article are:

- To develop a case for the applicability of game theory to ad hoc networks.
- To list the benefits and challenges of applying game theory to ad hoc networks.
- To survey the recent literature on game-theoretic analysis of ad hoc networks and summarize its general conclusions.

Components of a game	Elements of an ad hoc network
Players	Nodes in the network
Strategy	Action related to the functionality being studied (e.g., the decision to forward packets or not, the setting of power levels, the selection of waveform/modulation scheme)
Utility function	Performance metrics (e.g., throughput, delay, target signal-to-noise ratio)

■ Table 2. *Typical mapping of ad hoc network components to a game.*

- To provide a game theoretic perspective on incentive schemes for ad hoc networks.
- To illustrate the application of game theory to different layers in the protocol stack by means of game formulations.

We structure the remainder of the article as follows. We describe the components of an ad hoc network game and highlight benefits of game theory and challenges in the parameterization of the game. We describe the current state of research in the development of game theoretic models for solving problems at different protocol layers. We provide a brief description of existing incentive mechanisms for ad hoc networks and the use of game theory in analyzing them. We point to additional research issues in the application of game theory to ad hoc networks.

MODELING AD HOC NETWORKS AS GAMES

In a game, players are independent decision makers whose payoffs depend on other players' actions. Nodes in an ad hoc network are characterized by the same feature. This similarity leads to a strong mapping between traditional game theory components and elements of an ad hoc network. Table 2 shows typical components of an ad hoc networking game.

Game theory can be applied to the modeling of an ad hoc network at the physical layer (distributed power control and waveform adaptation), link layer (medium access control), and network layer (packet forwarding). Applications at the transport layer and above exist also, although less pervasive in the literature. A question of interest in all those cases is that of how to provide the appropriate incentives to discourage selfish behavior. Selfishness is generally detrimental to overall network performance; examples include a node's increasing its power without regard for interference it may cause on its neighbors (layer 1), a node's immediately retransmitting a frame in case of collisions without going through a backoff phase (layer 2), or a node's refusing to forward packets for its neighbors (layer 3). In the next section we outline game-theoretic models for these three layers. Before that, however, we discuss some of the benefits and common challenges in applying game theory to the study of ad hoc networks.

BENEFITS OF APPLYING GAME THEORY TO AD HOC NETWORKS

Game theory offers certain benefits as a tool to analyze distributed algorithms and protocols for ad hoc networks. We highlight three of those benefits:

Analysis of distributed systems: Game theory allows us to investigate the existence, uniqueness, and convergence to a steady state operating point when network nodes perform independent adaptations. Hence it serves as a strong tool for a rigorous analysis of distributed protocols.

Cross layer optimization: Often in ad hoc networking games, node decisions at a particular layer are made with the objective of optimizing performance at some of the other layers. With an appropriate formulation of the action space, game-theoretic analysis can provide insight into approaches for cross layer optimization.

Design of incentive schemes: Mechanism design is an area of game theory that addresses the engineering of incentive mechanisms that will lead independent, self-interested participants toward outcomes that are desirable from a system-wide perspective. This may prove especially helpful in the design of incentive schemes for ad hoc networks. We provide further discussion of incentive schemes later.

CHALLENGES IN APPLICATION OF GAME THEORY TO AD HOC NETWORKS

The use of game theory to analyze the performance of ad hoc networks is not without its challenges. We point out three particularly challenging areas:

Assumption of rationality: Game theory is founded on the hypothesis that players act rationally, in the sense that each player has an objective function that she tries to optimize given imposed constraints on its choices of actions by conditions in the game. Although nodes in an ad hoc network can be programmed to act in a rational manner, the steady-state outcome of rational behavior need not be socially desirable. Indeed, a major contribution of game theory is that it formally shows that individually rational, objective-maximizing behavior does not necessarily lead to socially optimal states.

The assumption of perfect rationality, on some practical occasions, does not accurately reflect empirically observed behavior (e.g., widespread existence of peer-to-peer file sharing networks in the absence of any punishment/reward schemes). The work in [2] considers an extension of the NE concept in order to accurately model nodes that deviate slightly from their expected optimal behavior. This form of weakened rationality is known as near-rationality.

Realistic scenarios require complex models: The dynamic nature of ad hoc networks leads to imperfection or noise in actions observed by a node. Such imperfections need to be modeled with reasonably complex games of imperfect information and/or games of imperfect monitoring. In addition, modeling of wireless channel models and interactions between protocols at the different layers involves complex and, at times, non-linear mathematical analysis.

Choice of utility functions: It is difficult to assess how a node will value different levels of performance and what trade-offs it is willing to make. The problem is exacerbated by a lack of analytical models that map each node's available actions to higher-layer metrics such as throughput.

GAME THEORY IN AD HOC NETWORKS: A LAYERED PERSPECTIVE

In this section we summarize potential applications of game theory to ad hoc networks, discussing issues at each layer in the protocol stack.

PHYSICAL LAYER

Distributed power control and selection of an appropriate signaling waveform are physical layer adaptations that may be

Symbol	Meaning	Symbol	Meaning
N	The set of decision making nodes in the network; $\{1, 2,\ldots, n\}$.	$\mathbf{P}$	The power space ($\mathcal{R}$) formed from the Cartesian product of all $\mathbf{P_j}$. $\mathbf{P} = \mathbf{P}_1 \times \mathbf{P}_2 \times \ldots \times \mathbf{P_n}$
h_{ij}	The link gain from i to j. Note this may be a function of the waveform selected.	$\mathbf{p}$	A power profile (vector) from $\mathbf{P}$ formed as $\mathbf{p} = (p_1, p_2, \ldots, p_n)$.
H	The network link gain matrix. $H = \begin{bmatrix} 1 & h_{12} & h_{13} & \ldots & h_{1n} \\ h_{21} & 1 & & & \vdots \\ h_{31} & & \ddots & & \\ \vdots & & & \ddots & \\ h_{n1} & h_{n2} & \ldots & \ldots & 1 \end{bmatrix}.$	$\mathbf{\Omega_j}$	The set of waveforms known by node j.
		ω_j	A waveform chosen by j from $\mathbf{\Omega_j}$.
		$\mathbf{\Omega}$	The waveform space formed from the Cartesian product of all $\mathbf{\Omega_j}$. $\mathbf{\Omega} = \times_{j \in N} \mathbf{\Omega_j}$.
$\mathbf{P_j}$	The set of power levels available to node j. This is presumed to be a subset of the real number line.	$\boldsymbol{\omega}$	A waveform profile (vector) from $\mathbf{\Omega}$ formed as $\boldsymbol{\omega} = (\omega_1, \omega_2, \ldots, \omega_n)$.
p_j	A power level chosen by j from $\mathbf{P_j}$.	$u_j(\mathbf{p}, \boldsymbol{\omega}, H)$	The utility derived by j.

Table 3. *Game theoretic model for physical layer adaptations in ad hoc networks.*

adopted by a node. From a physical layer perspective, performance is generally a function of the effective signal-to-interference-plus-noise ratio (SINR) at the node(s) of interest. When the nodes in a network respond to changes in perceived SINR by adapting their signal, a physical layer interactive decision making process occurs. This signal adaptation can occur in the transmit power level and the signaling waveform (modulation, frequency, and bandwidth). The exact structure of this adaptation is also impacted by a variety of factors not directly controllable at the physical layer, including environmental path losses and the processing capabilities of the node(s) of interest. A game theoretic model for narrowband physical layer adaptations can be formed using the parameters listed in Table 3.

From Table 3, the stage game for interactive physical-layer adaptations can be modeled as

$$G = \langle N, \{\mathbf{P_j} \times \Omega_\mathbf{j}\}, \{\mathbf{p}, \boldsymbol{\omega}, H)\}\rangle$$

For a general physical layer adaptation game, each node, j, selects a power level, p_j, and a waveform, ω_j, based on its current observations and decision making process. Restricted versions of this game are commonly encountered in the literature. Distributed power control systems permit each radio to select p_j, but restrict $\mathbf{\Omega_j}$ to a singleton set; distributed waveform adaptation systems (adaptive interference avoidance) restrict the choice of p_j, but allow ω_j to be chosen by the physical layer.

Power Control — Power control, though closely associated with cellular networks, is frequently implemented in ad hoc networks due to the potentially significant performance gains achieved when nodes limit their power level [3]. The following discussion applies to several proposed distributed power control schemes. Although not all of these works adopt a game theoretic approach, the distributed nature of different proposed algorithms lends itself to the application of game theory.

In [4] an algorithm for performing distributed power control in 802.11 networks is described. The authors permit the use of ten different power levels and incorporate the necessary signaling into the exchange of RTS-CTS-DATA-ACK frames. Each node communicates with its neighbor nodes and chooses a transmit level for each neighbor in such a way that the minimum signal power required for acceptable performance is achieved. In this scenario each node can be modeled as attempting to achieve a target SINR. Although not considered in [4], this could be modeled using multiple connection reception scenarios as suggested by [5], or each connection could be treated as a unique entity in the fixed assignment scenario.

A similar algorithm has been proposed by [6], wherein an additional channel is included for power control. Likewise, in [7] the authors introduce "Noise Tolerance Channels" that are analogous to a power control channel, but instead permit each node to announce its amount of "noise" tolerance, i.e. the additional interference that can be afforded without losing a currently received signal. Other authors, such as in [8] and [9], have further refined the ad hoc power control problem by introducing beam forming considerations.

We now model the power control algorithm suggested in [4] as a normal form game. Note that a similar approach can be followed to model the other distributed algorithms as games, with each game involving a different utility function. We adopt the notation in Table 3. Here, we are assuming that each node, i, in the set of nodes, N, is maintaining a single link to its node of interest, v_i. As each node is attempting to maintain a target SINR, an appropriate utility function for it is given by:

$$u_i(\mathbf{p}) = -\left[\hat{\gamma}_i - \frac{h_{iv_i} p_i}{\sigma_{v_i} + \sum_{j \in N, j \neq i} h_{jv_i} p_j}\right]^2$$

where σ_{v_i} is the noise at v_i and $\hat{\gamma}_i$ is the target SINR of player i. A game model for this algorithm is thus given by $G = \langle N, \mathbf{P}, \{u_i\}\rangle$.

We can quickly verify that G has at least one NE by applying the Glicksberg-Fan fixed point theorem [10, 11]. Assuming the target SINRs are feasible, then the power vector corresponding to G's unique NE can be found by solving the linear program given by

$$Z\bar{\mathbf{p}} = \bar{\boldsymbol{\gamma}}$$

where

$$Z = \begin{bmatrix} h_{1v_1} & -\hat{\gamma}_1 h_{1v_2} & \cdots & -\hat{\gamma}_1 h_{1v_n} \\ -\hat{\gamma}_2 h_{2v_1} & h_{2v_2} & \cdots & -\hat{\gamma}_2 h_{2v_n} \\ \vdots & \vdots & \ddots & \vdots \\ -\hat{\gamma}_n h_{nv_1} & -\hat{\gamma}_n h_{nv_2} & \cdots & h_{nv_n} \end{bmatrix},$$

$$\bar{\boldsymbol{\gamma}} = \left[\hat{\gamma}_1\sigma_{v_1}\ \hat{\gamma}_2\sigma_{v_2}\ \ldots\ \hat{\gamma}_n\sigma_{v_n}\right]^T, \text{ and } \bar{\mathbf{p}} = [p_1 p_2 \ldots p_n]^T.$$

While the surveyed algorithms are for ad hoc networks, most power control games, except recent work in [12] and [13], consider infrastructure-based wireless networks. When choosing a distributed algorithm for a network, several factors should be considered, including steady-state performance, convergence, complexity, stability, and interaction with other layers' behavior. These form some of the active areas of research within the field of distributed power control and game theory.

Waveform Adaptation — Waveform adaptation in ad hoc networks involves the selection of a waveform by a node such that the interference at its receiver is reduced. The interference at the receiver is a function of the correlation of a user's waveform with the waveforms of the other users in the network. Also, in general, the individual nodes involved in transmission have no or very little information about the receiver's interference environment. Hence, to minimize the adaptation overhead, distributed waveform adaptation algorithms that require a minimal amount of feedback between receivers and transmitters need to be developed for these networks. Game theory can provide useful insights into this scenario.

Past work on interference avoidance has concentrated on single-receiver systems. A distributed interference avoidance algorithm for the uplink of a synchronous CDMA system with a single base-station is proposed in [14]. In this algorithm, each node sequentially updates its signature sequence to improve its SINR at the base-station. The signature sequences represent code-on-pulse spreading codes with chips taking any value in the complex plane. This iterative algorithm (wherein users greedily increase their SINR) converges to a set of sequences that maximize the sum capacity of the system [15]. Further, this approach is generalized to the situation where nodes can adapt their modulation/demodulation methods using a general signal space approach. Other extensions include sequence adaptation in asynchronous CDMA systems [16], multipath channels [17], and multi-carrier systems [18].

The use of game theory provides us with a better analysis of the greedy signature update mechanism and helps us derive convergence conditions. Game theory has been used to show that for a single receiver system with two players, any combination of the metric (such as Mean Square Error or SINR) and receiver types (such as a correlator or MSINR receiver) results in a game with convergent Nash equilibrium solutions [19]. A game-theoretic framework to analyze power control and signature sequence adaptation in synchronous CDMA systems is also presented in [20]. Properties of the utility function associated with each user in the network that ensure the existence of a Nash equilibrium for the power and waveform adaptation game are identified, with Signal to Interference and Noise Ratio (SINR) possessing these properties.

Convergent Nash equilibria are thus seen to exist in greedy waveform adaptation games in a single centralized receiver scenario. However, in networks with multiple distributed receivers, application of the same greedy interference avoidance techniques does not lead to a stable NE ([21, 22]) due to the asymmetry of the mutual interference between users at different receivers (for instance, a user causes more interference at a nearby receiver than at a receiver that is farther away). This leads to users' adapting their sequences in conflicting ways. This shows that greedy interference schemes cannot be directly extended to ad hoc networks. A framework based on potential game theory such as the one described here can be used to construct convergent waveform adaptation games in such a scenario. We refer the reader to [23] for a detailed discussion.

A potential game [24] is a normal form game such that any change in the utility function of any player due to a unilateral deviation by that player is correspondingly reflected in a global function, referred to as the potential function. The existence of a potential function makes this type of game easy to analyze and provides a framework in which users can serve the greater good by following their own best interest, i.e., maximize a global utility by only trying to maximize their own utilities. Hence, it can lead to simple game formulations where maximizing the utility of users also improves a global network performance measure. There are a number of different types of potential games, of which exact and ordinal potential games are considered in this section.

Exact and ordinal potential games possess a useful convergence property: players of the game are guaranteed to converge to a NE by playing their best response. This assures that the waveform adaptation games constructed according to the framework described below always converge. We will derive a potential function for the waveform adaptation scenario to formulate it as a potential game. Again, we adopt the notation in Table 3. Let the utility associated with a particular user be given by

$$u_i(\omega_i, \boldsymbol{\omega}_{-\mathbf{i}}) = f_1(\omega_i) - \sum_{j=1, j\neq i}^{N} f_2\left(I\left(\omega_j, \omega_i\right), p_d, p_i, h_{ji}\right) - \sum_{j=1, j\neq i}^{N} \gamma_{ij} f_3\left(I\left(\omega_j, \omega_i\right), p_i, p_j, h_{ij}\right)$$

where: f_1 quantifies the benefit associated with a particular choice of signature sequence; f_2 is the interference measure for user i perceived at its associated receiver due to the other users present in the system; I is a function of two signature sequences ω_i and ω_j (for instance, the correlation between sequences); and function f_3 is the interference caused by a particular user i at the receivers associated with other users. In this framework, the transmit power of a user is assumed to be fixed and independent of the waveform adaptation process.

Let $\overline{\omega}_i$ be the new signature sequence chosen by user i. Then by the definition the game is an exact potential game if there exists a potential function $Pot(\boldsymbol{\omega})$ such that

$$u_i(\omega_i, \boldsymbol{\omega}_{-\mathbf{i}}) - u_i(\overline{\omega}_i, \boldsymbol{\omega}_{-\mathbf{i}}) = Pot(\omega_i, \boldsymbol{\omega}_{-\mathbf{i}}) - Pot(\overline{\omega}_i, \boldsymbol{\omega}_{-\mathbf{i}}) \forall i$$

A candidate potential function, if $f_2(\bullet) = f_3(\bullet)$, is given by

$$Pot(\boldsymbol{\omega}) = \sum_{i=1}^{N}\left(f_1(\omega_i) - \sum_{j=1, j\neq i}^{N} f_2\left(I\left(\omega_i, \omega_j\right), p_i, p_j, h_{ji}\right)\right)$$

The game is an ordinal potential game if

$$u_i(\omega_i, \boldsymbol{\omega}_{-\mathbf{i}}) \geq u_i(\overline{\omega}_i, \boldsymbol{\omega}_{-\mathbf{i}}) \Leftrightarrow Pot(\omega_i, \boldsymbol{\omega}_{-\mathbf{i}}) \geq Pot(\overline{\omega}_i, \boldsymbol{\omega}_{-\mathbf{i}}) \forall i$$

Let the utility function for a user for an ordinal potential game formulation be given by

$$u_i(\omega_i, \boldsymbol{\omega}_{-\mathbf{i}}) = f_1(\omega_i) - \sum_{j=1, j\neq i}^{N} f_{2i}\left(I\left(\omega_j, \omega_i\right), p_j, p_i\right) - \sum_{j=1, j\neq i}^{N} f_{3i}\left(I\left(\omega_i, \omega_j\right), p_i, p_j\right)$$

where f_{2i} is the interference measure for user i perceived at its associated receiver due to the other users present in the system, and function f_{3i} is the interference caused by user i at the receivers associated with other users. Note that functions f_{2i} and f_{3i} can be different for different users.

The condition for an ordinal potential game is satisfied if $f_{2i}(\bullet) = f_{3i}(\bullet)$ and $f_{2i}(\bullet)$ and is any ordinal (monotonically increasing) transformation of $f_{pot}(\bullet)$ where the potential function is given by

$$Pot(\boldsymbol{\omega}) = \sum_{i=1}^{N}\left(f_1(\omega_i) - \sum_{j=1, j\neq i}^{N} f_{pot}\left(I\left(\omega_i, \omega_j\right), p_i, p_j\right)\right)$$

This ordinal potential game formulation can be used to construct convergent adaptation games with each user trying to maximize a different utility function, as long as the utility functions are ordinal transformations of each other.

The authors in [21] present a distributed sequence adaptation algorithm for networks with no centralized receiver. The user's utility function is defined in terms of a new interference measure. This interference measure is the weighted sum of the interference caused by the particular user at all the receivers in the system. It is shown that an increase in the utility of any user also results in the increase of a social function (similar to the potential function), which is the sum of the utilities of all the users in the system, proving the existence of NE for the system. It can be shown that this adaptation algorithm is a specific instance of the family of waveform adaptation games represented by the above mentioned game-theoretic framework.

Feedback is also a significant issue in the implementation of distributed interference avoidance algorithms. The signature sequence (in the case of the centralized receiver model) or the signature correlation matrix (in the case of multiple uncoordinated receivers) is required to provide feedback to each user. This could place a prohibitively expensive burden on network overhead. The work in [25] proposes that restricting each user's waveform to a subspace of the waveform's original signal space may relieve this burden. Alternately, properties of games such as better response convergence of potential games can be used to design reduced feedback schemes [26].

It is not difficult to envision that many more complex systems for reducing interference by appropriate selection of waveforms could help. However, for each new proposed system, the same issues of convergence and stability will need to be considered. Game theory has the potential to address these questions in a formal manner.

MEDIUM ACCESS LAYER

The medium access control problem, with many users contending for access to a shared communications medium, lends itself naturally to a game theoretic formulation. In these medium access control games, selfish users seek to maximize their utility by obtaining an unfair share of access to the channel. This action, though, decreases the ability of other users to access the channel.

One of the earliest applications of game theory to a medium access control problem is the work of Zander in [27] and [28]. However, the game considered is cooperative in nature and does not consider contention between selfish nodes themselves. MacKenzie and Wicker pose the slotted Aloha medium access control protocol itself as a game between users contending for the channel in [29, 30], and [31]. In their work, users receive a one unit payoff when they transmit successfully and attempt to maximize the discounted sum of their payoffs over time; the infinite users' model is adopted with a finite arrival rate. If transmissions are costless, then users jam the channel with transmission attempts, resulting in extremely low throughput. If there is a transmission cost that must be paid in order to transmit (e.g., energy from a battery), then the maximum throughput that can be supported by the system can be computed. The authors concluded that, for optimal values of the cost parameter, the throughput of a slotted-Aloha system with non-cooperative users may be as high as the throughput that can be obtained with cooperative users. This work was expanded to CSMA and CSMA/CD in [32] and forthcoming papers.

Here we will briefly examine the analysis of slotted Aloha; for more details the reader should refer to [31]. In a given slot, each user has two possible actions: the user can transmit or wait. If exactly one user chooses to transmit in a given slot, then that user's transmission is successful. If multiple users transmit in a slot, then all of their transmissions are unsuccessful. We assume that the payoff associated with a successful transmission is 1, while the cost of transmission (whether successful or unsuccessful) is c, where $0 < c < 1$. A user who waits will receive a payoff of 0; a user who transmits will receive a payoff of either $1 - c$ (if the transmission is successful) or $-c$ (if the transmission is unsuccessful). It is also assumed that each user has a discount factor $0 < \delta < 1$ that is used to discount future payoffs. So, the present value of waiting for 10 slots and then transmitting with certain success is $(1 - c)\delta^{10}$. The goal of a user is to maximize the expected discounted value of her payoff.

A strategy in this game is then a mapping from the number of backlogged users (assumed to be known) to a transmit probability; that is, a strategy is a function $p: Z^{+} \rightarrow [0,1]$. Given a particular Poisson packet arrival rate λ, a current backlog n, and a strategy q being followed by all other users, a user can compute an expected payoff to a particular strategy p. In order for a strategy p to be an equilibrium strategy, it must be the case that p maximizes the expected payoff for a player if all other players are also playing p. This assumes that all players are indistinguishable. The Glicksberg-Fan fixed point theorem [10, 11] can be invoked to prove that such an equilibrium must exist. In order to apply the theorem, the following conditions must be satisfied: a finite player set; a compact and convex action space; and continuous utility functions for each player that are quasi-concave. While quasi-concavity may not be a familiar concept, it is just a generalization of the more familiar concavity concept, as all concave functions are also quasi-concave.

It is easy to see that if there are at least two users backlogged ($n \geq 2$) then neither "always transmit" nor "always wait" can be equilibrium strategies p. In other words, for $n \geq 2$, $0 < p(n) < 1$. It is also well known, though, that in order for a mixed strategy to be played in a given scenario, it must be the case that the expected payoffs must be equal from all of the pure strategies in support of the mixed strategy. Hence, for $n \geq 2$ the payoff from transmitting must equal the payoff from waiting. If the value of the backlog is large, then obviously the expected payoff of an equilibrium strategy must be near zero. Glossing over some mathematical details presented in [31], it is then possible to prove the intuitively appealing result that the expected payoff when transmitting (which is the probability of transmission success) is equal to the transmission cost. That is, in the limit as $n \to \infty$ for an equilibrium strategy p we must have:

$$(1 - p(n))^{n-1} \to c$$

In other words, for large n we must have:

$$p(n) \to \frac{-\ln c}{n}$$

It follows immediately that the throughput of the slotted Aloha system (equal to $np(n)(1 - p(n))^{n-1}$) will go to $-c\ln c$ as $n \to \infty$. A drift analysis can formalize this argument to show that the slotted Aloha system will be stable whenever $\lambda < -c\ln c$. It follows that if $c = e^{-1}$, then the system will be stable for arrival rates up to e^{-1}. In other words, for the right value of c, the throughput of a slotted Aloha system with selfish users is exactly the same as the throughput of a system in which the users work together to maximize system throughput.

This result has been generalized in [31] to show that the same result holds for other channels (e.g., when capture is possible in the presence of two or more transmissions). The result suggests that it may not, in fact, be necessary to assume that nodes are cooperative in order to design an efficient random access protocol.

One of the main criticisms of the work of MacKenzie and Wicker is their assumption that the number of backlogged users is known. The work in [33] considers an alternative model in which the number of backlogged users is unknown, but the total number of users in the system is known and the users' retransmit probabilities are static rather than dynamic. They also show that if transmissions are costly, then the non-cooperative equilibrium throughput may coincide with the throughput obtained by cooperative users.

In an alternative model, [34] considers heterogeneous users who attempt to obtain a target throughput by updating their transmit probabilities in response to observed activity. Once the users' targets are fixed, potential methods are used to show that the updating process will converge to a vector of equilibrium transmit probabilities. They also investigate the question of when the users are able to attain their throughput targets. Furthermore, the authors in [35] assume that users' throughput targets depend on their utility functions and their willingness to pay, and they describe a pricing strategy to control the behavior of the users (in order to bring their targets within the feasibility region).

The work in [36] considers the problem that arises when non-cooperative nodes are introduced into a network of mostly cooperative users. Specifically, a MAC protocol called Random Token with Extraneous Collision Detection (RT/ECD) is considered, which is quite similar to the CSMA/CA protocol utilized by the distributed coordination function of IEEE 802.11. That work also proposes a variant of RT/ECD, denoted RT/ECD-1s, which enables cooperative nodes to maintain a higher share of the bandwidth in the presence of non-cooperative nodes. Recent work in [37] proposes a game-theoretic model to address the problem of selfish node behavior in CSMA/CA with nodes adjusting the random back-off timers to increase throughput. The authors derive a Pareto optimal point of operation for such a network and apply a repeated game approach to transform the Pareto optimal point into a Nash equilibrium.

As one can observe, the papers address a variety of different problems using several different game-theoretic models and approaches. It can also be seen that there are many areas open for future work. Specifically, the issue of imperfect information with a reasonable feedback model such as ternary feedback (0, 1, e) has not been suitably addressed. While random access protocols such as those typically used in LANs have been modeled, scheduled access problems such as channel or time-slot assignment have not been adequately addressed.

Network Layer

Functionalities of the network layer include the establishment and updating of routes and the forwarding of packets along those routes. Issues such as the presence of selfish nodes in a network, convergence of different routing techniques as the network changes, and the effects of different node behavior on routing, have been analyzed using game theory. We discuss these next.

Modeling of Traditional Routing Techniques Incorporating Ad Hoc Network Characteristics — A recent application of game theory to ad hoc routing [38] focuses on the analysis of the effectiveness of three ad hoc routing techniques, namely link state routing, distance vector routing, and multicast routing (reverse path forwarding), in the event of frequent route changes. The objective of the analysis is to compare and contrast the techniques in an ad hoc setting. These techniques are evaluated in terms of:

- Soundness: whether routers have a correct view of the network to make the correct routing decisions under frequent network changes.
- Convergence: the length of time taken by the routers to have a correct view of the network topology as nodes move.
- Network overhead: the amount of data exchanged among routers to achieve convergence.

Routing is modeled as a zero sum game between two players — the set of routers and the network itself. In a zero-sum game [1] the utility function of one player (minimizing player) is the negative of the other's (maximizing player). The game has an equilibrium when the minmax value of any player's payoff is equal to its maxmin value. In a zero sum game, the maxmin value is defined as the maximum value that the maximizing player can get under the assumption that the minimizing player's objective is to minimize the payoff to the maximizing player. In other words, the maxmin value represents the maximum among the lowest possible payoffs that the maximizing player can get; this is also called the safe or secure payoff.

In the routing game the payoff to each player consists of two cost components, one being the amount of network overhead and the other varying with the performance metric under consideration. For example, for evaluating soundness the cost to the routers is 0 if all routers have a correct view of the topology when the game ends, and 1 if any one router does not. The objective of the routers is to minimize the cost function. The action for the routers involved is to send routing control messages as dictated by the routing technique and update their routing information, and for the network to change the state of existing links from up to down and vice versa. The game is solved to determine the minmax value of the cost function. It serves to compare the different routing techniques in terms of the amount of routing control traffic

Symbol	Meaning
N	The set of nodes in the ad hoc network; $\{1, 2, \ldots n\}$
S_k	Action set for node k; $S_k = \{0,1\}$.
s_k	Action of node k: $s_k = 0$ (not participate) and $s_k = 1$ (participate).
$\mathbf{S}$	Joint action set; $\mathbf{S} = \times_{k \in N} S_k$.
$\mathbf{s}$	$\mathbf{s} = \{s_1, s_2, \ldots, s_n\}$; $\mathbf{s} \in \mathbf{S}$.
$\alpha_k(\mathbf{s})$	Benefit accrued when other nodes participate; $\left(e.g., \; \alpha_k(\mathbf{s}) = \sum_{i=1, i \neq k}^{n} s_k\right)$.
$\beta_k(\mathbf{s})$	Benefit (or cost) to node k when it participates; for energy constrained nodes it is negative (e.g., $\beta_k(\mathbf{s}) = -s_k$).
$u_k(\mathbf{s})$	Utility of the node; $u_k(\mathbf{s}) = \alpha_k(\mathbf{s}) + \beta_k(\mathbf{s})$.

■ Table 4. *Game theoretic model for node participation in ad hoc networks.*

required to achieve convergence and the soundness of the routing protocol to network changes. One of the main conclusions reached in the comparative analysis was that reverse path forwarding requires less control traffic to achieve convergence, against traditional link state routing.

Another issue related to routing involves studying the effect of selfish nodes on the forwarding operation, as discussed next.

Selfish Behavior in Forwarding Packets — The establishment of multi-hop routes in an ad hoc network relies on nodes' forwarding packets for one another. However, a selfish node, in order to conserve its limited energy resources, could decide not to participate in the forwarding process by switching off its interface. If all nodes decide to alter their behavior in this way, acting selfishly, this may lead to the collapse of the network. The works of [39–44] develop game theoretic models for analyzing selfishness in forwarding packets. Under general energy-constraint assumptions, the equilibrium solution for the single-stage game results in none of the nodes' cooperating to forward packets. A typical game theoretic model that leads to such an equilibrium is parameterized in Table 4. Now, consider strategy $\bar{\mathbf{s}} = \{\bar{s}_1, \bar{s}_2, \bar{s}_3, \ldots \bar{s}_n\}$ and let $\sigma = \{k \in N \,|\bar{s}_k = 1\}$. The utility of any node $k \in \sigma$ is given by

$$u_k(\bar{\mathbf{s}}) = (|\sigma| - 1) - s_k = |\sigma| - 2$$

Let us consider that node k unilaterally deviates to a strategy of not participating. The utility of node k is given by $u_k(s'_k, \bar{\mathbf{s}}_k) = |\sigma| - 1$. Since $u_k(s'_k, \bar{\mathbf{s}}_{-k}) > u_k(\bar{\mathbf{s}})$, strategy $\bar{\mathbf{s}}$ can only be a Nash equilibrium when $\sigma = \phi$.

However, in practical scenarios ad hoc networks involve multiple interactions among nodes/players with a need for nodes to participate. In order to account for such interactions, the basic game is extended to a repeated game model. Different repeated game mechanisms such as tit-for-tat [45] and generous tit-for-tat are investigated in [40, 42] and [43] to determine conditions for a desirable NE, one in which all nodes would forward packets for one another leading to a high network-wide social welfare. The tit-for-tat-based mechanisms provide an intrinsic incentive scheme where a node is served by its peers based on its past behavioral history. As a result, a node tends to behave in a socially beneficial manner in order to receive any benefit in the later stages.

The work in [46] extends this concept of exploiting the intrinsic "fear" among nodes of being punished in the later stages of the game by deriving the conditions under which a grim-trigger strategy is a Nash equilibrium in a game where nodes are asked to voluntarily provide services for others. (Examples of these include peer-to-peer networks and distributed clusters, as well as ad hoc networks.) A node following the grim trigger strategy in a repeated game is characterized by a behavior wherein it continues to cooperate with other nodes until a single defection by any of its peers, following which it ceases to cooperate for all subsequent stages. The sustainability of the equilibrium for this strategy depends on the number of nodes in the network and the exogenous beliefs that the nodes have regarding the possible repetitions of the game. The authors conclude that the greater the number of nodes in the network the higher the chances of achieving a desirable equilibrium, even if the likelihood that the game will be repeated is low. These games are different from those analyzed in [41] and [44] as the decisions of the nodes are not based on an external incentive scheme such as reputation.

Other functions related to the network layer or to the management plane, such as service discovery and policy-based network management, are also amenable to a game-theoretic analysis. There is scarce literature on those issues, with the notable exception of [47], which studies management in a sensor network.

Transport Layer

At the transport layer, game-theoretic models have been developed to analyze the robustness of congestion control algorithms to the presence of selfish nodes in the network. However, the bulk of the research has been focused on wired networks [48–50]. That research could serve as a starting point in the development of a game-theoretic model to analyze congestion control for ad hoc networks, but it is important to take into consideration the de-centralized nature of the network and the trade-offs that accompany it.

Focusing the research on a completely independent node set-up, the game formulated in [50] comprises nodes capable of individually varying their congestion window additive increase and multiplicative decrease parameters with the objective of increasing their throughput. The effect of such behavior in conjunction with buffer management policies implemented at the routers is studied for congestion control algorithms such as TCP-Reno, TCP-Tahoe, and TCP-SACK. However, when applying the conclusions to wireless ad hoc networks it is necessary to consider the impact of the wireless medium on TCP. Link failures due to mobility and packet losses caused by impairments of the wireless medium could inadvertently trigger a change in the congestion window. Therefore in the development of a TCP congestion control game it will be necessary for a node to consider this effect before making its decision on setting the congestion control parameters. This could lead to a change in the model parameters and also affect the outcome of the game.

INCENTIVE MECHANISMS

Selfish behavior by nodes in an ad hoc network may lead to a suboptimal equilibrium [39, 40, 51] where nodes, through their actions, reach an undesirable steady state from a network perspective (in addition to often not being Pareto-optimal). Hence, incentive mechanisms are proposed to steer nodes toward constructive behavior (i.e., toward a desirable equilibrium). Incentive mechanisms are broadly divided into two categories based on their technique of incentivizing nodes: credit-exchange-based systems and reputation systems. We will briefly mention some of the incentive mechanisms proposed in the literature and describe how game theory has been applied to analyze the effectiveness of these incentive schemes.

CREDIT EXCHANGE

One of the techniques for providing incentives for nodes to behave in ways that are socially efficient (i.e., beneficial to the network as a whole) is to adopt a mechanism of charge and reward [52–56]. In such a scheme, a node is credited for cooperating with the other nodes toward a common network goal, and is debited when requesting service from others. One way of implementing the charge and reward scheme is by the introduction of "virtual currency" as in [52]. In this method each node is rewarded with "tokens" for providing service, which are then used by the node for seeking services from others. One criticism of this method is that it requires a tamper-proof hardware module to prevent nodes from cheating during "token" exchange. In addition, such techniques may be cumbersome to implement as charges and rewards are calculated on a per-packet basis [57].

In order to address the security vulnerability of nodes falsely reporting credit, the concept of algorithmic mechanism design is leveraged to design pricing policies that lead to truthful reporting. The authors in [53–56] develop incentive-compatible, cheat-proof mechanisms that apply the principles of mechanism design to enforce node collaboration for routing in ad hoc networks, with the suthors in [58] focusing on multicast routing. In addition, different pricing schemes (such as in [59, 60]) are often used to engineer an equilibrium that is desirable from the network's perspective. A detailed survey of various pricing schemes is outside the scope of this article.

REPUTATION–BASED MECHANISMS

Another technique for creating incentives is in the form of the reputation that each node gains through providing services to others. Each node builds a positive reputation for itself by cooperating with others and is tagged as "misbehaving" otherwise. The nodes that gain a bad reputation are then isolated from the network over time. Several reputation mechanisms can be found in the recent literature (such as in [41, 61–64]). Game theory has been used in [41] for the analysis of a reputation exchange mechanism. According to this mechanism, a node assigns reputation values to its neighbors based on its direct interactions with them and on indirect reputation information obtained from other nodes. Further, this reputation mechanism is modeled as a complex node strategy in a repeated game model. The analysis of the game helps to assess the robustness of the reputation scheme against different node strategies and derive conditions for cooperation.

There exist other mechanisms that do not involve any logical object (reputation, virtual currency) in inducing an optimal equilibrium. This includes the generous tit-for-tat mechanism (GTFT) [45], which has been proposed to solve the problem of misbehaving nodes in routing and forwarding. The authors in [42] employ the GTFT technique as a node strategy in a repeated game for forwarding packets, and conditions are derived for it to achieve a socially optimal Nash equilibrium.

A different approach to inducing a desirable equilibrium requires a centralized authority, i.e. a referee, to ensure that the nodes' behavior converges to an optimal operating point ([29] provides an application to wireless networks). This centralized controller is not a player and is external to the game. Typically, the external entity evaluates the strategy that will result in system-wide benefit and informs the nodes about it. In addition, it may also change the rules of the game dynamically during play to ensure optimality in the system. Such an approach is of limited applicability to an ad hoc environment, due to the assumption of central control. However, it may be possible to utilize existing cluster head selection algorithms to select the appropriate referees and thereby adapt this external equilibrium inducing mechanism to ad hoc networks.

CONCLUDING REMARKS

The application of mathematical analysis to wireless ad hoc networks has met with limited success, due to the complexity of mobility and traffic models, coupled with the dynamic topology and the unpredictability of link quality that characterize such networks. Emerging research in game theory applied to ad hoc networks shows much promise to help understand the complex interactions between nodes in this highly dynamic and distributed environment.

The application of game theory to analyze problems at different protocol layers in an ad hoc network is at a nascent stage, with the bulk of the work done in the past few years. The focus has been on maximizing throughput using random access techniques for the wireless medium, and on developing robust techniques to deal with selfish behavior of nodes in forwarding packets. Other areas to which game theory has been applied include distributed power control and interference avoidance.

There is significant interest in cross-layer optimizations for wireless networks. Game theory offers a tool to model adaptations that may occur at different layers of the protocol stack and to study convergence properties of such adaptations. Recently developed games such as potential games are finding a larger audience due to their properties regarding the existence of and convergence to a NE. Also, the employment of game theory in modeling dynamic situations for ad hoc networks where nodes have incomplete information has led to the application of largely unexplored games such as games of imperfect monitoring.

Some problems in ad hoc network security are good candidates for analysis employing game theory. Examples include the modeling of trust and reputation management schemes, and denial of service attacks and counter-measures. With recent interest in cognitive radios, we believe that game theory also has a strong role to play in the development and analysis of protocols for ad hoc networks equipped with such radios.

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