

A game-theoretic framework for opportunistic transmission in wireless networks

Ca Van Phan

Department of Electrical and Electronics Engineering
University of Technical Education Ho Chi Minh City, Vietnam
Email: capv@hcmute.edu.vn

Abstract—We propose a game-theoretic framework for opportunistic transmission strategy for wireless networks that operate in a strict energy-constrained environment. To reduce unsuccessful transmissions due to channel error and packet collision causing a waste of energy, the opportunistic transmission strategy attempts to transmit at good channel conditions while meeting the delay constraint under time-varying wireless channel. We formulate Constrained cost-coupled stochastic game to obtain the optimum threshold for successful transmission in the opportunistic transmission manner.

I. INTRODUCTION

In recent years, game theory has become an essential and effective tool for analyzing and designing wireless networks. In particular, there has been a rich literature using game theory to study medium access control. In [1], the authors have presented a game theoretic approach to design robust random access control protocols for wireless networks with fading channels. Specifically, the opportunistic transmissions in slotted ALOHA and CSMA adapted to channel information states are model as Bayesian games in which each transmission threshold is a Bayesian Nash equilibrium of the game. In [2], the authors have formulated a channel access game for transmission strategy with inter-cluster interference awareness in a decentralized manner and proved the existence of its Bayesian Nash equilibrium. The authors in [3] have formulated the problem of finding a transmission policy for each node in slotted ALOHA networks that maps the channel state information to transmission probabilities to maximize its individual utility as a noncooperative game. The condition for the existence of a Nash equilibrium threshold transmission policy has been given and a stochastic gradient based algorithm has been employed to handle the best response dynamic process for the transmission game. In [4] a game theoretic model exploiting the channel state information at each user to make decision on packet transmission in slotted ALOHA networks in a fading environment. In this model, each user sets a channel threshold and sends a packet only when the channel gain is higher than the threshold to maximize the net benefit of a user, utility minus power consumption.

Besides these approaches related to the transmission strategy above, some other approaches in [5]–[9] apply game theory to investigate contention control for wireless networks. In [5], the authors have presented a general game-theoretic model to study the interaction among the nodes contending for the common wireless channel. In addition, they have investigated the Nash equilibrium of this game and designed a method for achieving it in a distributed manner. The extension

of this work has been discussed in [6]. In this paper, the authors have generalized the game access control for the case where each node can observe multiple contention signals to guide them to the Nash equilibrium and given the conditions for the unique existence of this equilibrium. In [7]–[9], a novel concept of incompletely cooperative game theory has been proposed to improve the performance of CSMA/CA in mobile Ad Hoc Networks. In this game model, each node estimates the game state and changes its equilibrium by turning its contention parameters to achieve the optimal performance. The extension of this work has been shown in [9]. In this work, the authors have presented a method for estimating the conditional collision probability based on the Virtual-CSMA technique and proposed a simplified game theoretic MAC protocol that can be implemented in wireless mesh networks. A reverse-engineer of backoff-based random access MAC protocols using a game-theoretic approach has been presented in [10]. As shown in this paper, the exponential backoff protocol is reversed-engineered through a non-cooperative game in which each link tries to maximize a selfish local utility function. Additionally, the authors have proved the existence of the Nash equilibrium and provided sufficient conditions for its uniqueness and stability for the game.

The problem of the existence of selfish behaviors in wireless medium access control has also attracted attention of several researchers recently [11]–[14]. In [11], the authors have investigated the selfish behavior of nodes in CSMA/CA networks by using game theoretic approach and developed a localized and distributed protocol guiding multiple selfish nodes to a Pareto-optimal Nash equilibrium. A similar problem has been studied in [12] in which the backoff attacks in ad-hoc networks with anonymous stations have been analyzed in two different noncooperative game models: one-shot and repeated CSMA/CA games. Further, the authors have developed a strategy for stations, which provides a fair Pareto efficient and subgame perfect Nash equilibrium of repeated CSMA/CA games. In [13], the authors have investigated the stability of CSMA/CA based wireless networks with selfish users engaging in a noncooperative CSMA/CA game. In this game, each user's price can dynamically changes according to the network congestion and power consumption status. In addition, a proposed iterative method had been guaranteed convergence to the unique Nash equilibrium. In [14], a one-shot random access game for wireless networks has been presented to study the behavior of the selfish nodes. Further, the authors have analyzed thoroughly the channel throughput at Nash equilibria and also provided the asymptotic analysis of the game as the number of selfish transmitters goes to

infinity. In addition, Constrained cost-coupled stochastic game in which each player associates with an own Markov chain controlled by its own actions has been studied in [15]. At each time instants, each player determines an action according to some strategies to minimize the cost function under some constrains on its strategies. The interaction between a number of different players are coupled in their cost functions.

Our contributions of this work focuses on mathematically analyzing the behavior of the opportunistic transmission strategy (OTS) with the delay constraint in the context of time-varying wireless channel and delay-sensitive applications. In OTS scheme, before sending a packet the sender makes a decision on whether to send the packet at current time slot or to defer this transmission based on the channel state to minimize the energy consumption under buffer overflow constraint. The behavior of OTS scheme is formulated as Constrained cost-coupled stochastic game based on Markov decision process to obtain the optimal transmission policies.

II. SYSTEM MODEL

We consider an ad hoc network in which N mobile nodes use a slotted MAC protocol to access a common channel. In such network, time axis is divided into time slots of equals length of T_f seconds and all mobile nodes are synchronized to the same time slot reference. Whenever the mobile node has a pending packet to send, it will take either of two actions: Transmit and Defer, corresponding to transmitting the packet and deferring the transmission, respectively based on its local channel state information (CSI). It is assumed that the CSI is given at each node at the beginning of each time slot. In addition, the time slot is assumed to be sufficiently short and the traffic load is light such that the packet arrives at each time slot following a Bernoulli distribution with parameter q_a . We also assume that the outcome of traffic contribution is immediately available at the end of each time slot.

A finite-state Markov channel (FSMC) model as shown in Fig. 1 is used to capture the time-varying behavior of wireless fading channel [16]. In Rayleigh fading channels, the received instantaneous SNR (y) is exponentially distributed with pdf:

$$f_y(y) = \frac{1}{\rho} e^{-\frac{y}{\rho}}$$

where $\rho = E[y]$. Let y_i denote the threshold of the received SNR where $0 = y_0 < y_1 < y_2 < \dots < y_K = \infty$. The channel is said to be in state g_k , $0 \leq k < K$, if the received SNR is in the interval $[y_k, y_{k+1})$. We assume that the transitions in the FSMC model occur at the boundary of time slot in which one fixed-size frame is transmitted and transitions occurs only between adjacent states. Furthermore, the channel gain is constant during one time slot of transmission. The parameters of the Markovian channel can be obtained by using the techniques in [16].

The state transition probabilities are given by

$$\begin{aligned} P_g(k, k+1) &= \frac{T_f}{\pi_k} \sqrt{\frac{2\pi y_{k+1}}{\rho}} f_m e^{-\frac{y_{k+1}}{\rho}}, & 0 \leq k \leq K-2 \\ P_g(k, k-1) &= \frac{T_f}{\pi_k} \sqrt{\frac{2\pi y_k}{\rho}} f_m e^{-\frac{y_k}{\rho}}, & 1 \leq k \leq K-1 \end{aligned}$$

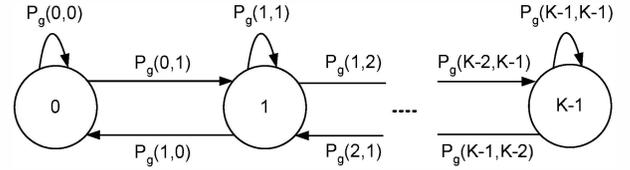


Fig. 1. Finite-state Markov channel model.

where f_m is the maximum Doppler frequency, T_f is the frame transmission time, and π_k is the steady-state probabilities given by

$$\pi_k = \int_{y_k}^{y_{k+1}} f_y(y) dy$$

For BPSK case, the probability of symbol error $P_b(g_k)$ for state g_k is given by

$$P_b(g_k) = \frac{\delta_k - \delta_{k+1}}{\pi_k} \quad (1)$$

where

$$\delta_k = e^{-\frac{y_k}{\rho}} \left(1 - F\left(\sqrt{2y_k}\right) \right) + \sqrt{\frac{\rho}{\rho+1}} F\left(\sqrt{\frac{2y_k(\rho+1)}{\rho}}\right)$$

and $F(x)$ denotes the cumulative distribution function (CDF) of a standard normal random variable. Throughout this paper the error statistics follow the BPSK case as formulated above.

III. CONSTRAINED COST-COUPLED STOCHASTIC GAME

In this model we consider a network in which the buffer is capable of storing at most one frame at each node with regard to the applications that require the latest data. Thus the existing frame in the buffer is replaced by a new arrival frame. Delay sensitivity of traffic is modeled by imposing the lifetime of D time slots on each frame. This implies that a frame staying in the buffer longer than D time slots must be dropped. The state of node i at time slot t is denoted by

$$x_i = \langle g_i, n_i \rangle$$

where g_i is the channel state at time slot i , $0 \leq g_i < K$, and n_i is the state of mobile node at time slot i . The possible states of the mobile node include *Idle* and $(D+1)$ *Delay* states where D corresponds to the lifetime of frame. Let I and D_k ($k = 0, 1, \dots, D$) denote *Idle*, $(D+1)$ *Delay* states, respectively. The mobile node is said to be in k^{th} *Delay* state (denoted by D_k) when a frame is delayed by k time slots and in *Idle* state when no frame is present. Let $A_i(x_i)$ denote the set of all possible control actions for player i in state x_i . a_i is the control action taken at time slot i . Each action in $A(x_i)$ corresponds to the following values:

$$a_i = \begin{cases} 0, & \text{Defer} \\ 1, & \text{Transmit} \end{cases} \quad (2)$$

Let $P_n(n_i, n_{i+1}, a)$ denote the transition probability of mobile node state from n_i to n_{i+1} under the given control action a following by the state diagram shown in Fig. 2. Given the system state $x_i = \langle g_i, n_i \rangle$ and a control action a_i , the probability of the system being state $x_{i+1} = \langle g_{i+1}, n_{i+1} \rangle$ in next time slot is:

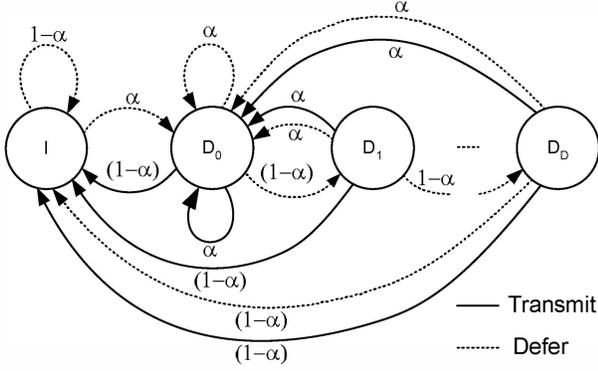


Fig. 2. State diagram of the transmission scheme with delay constraint.

$$\Pr [x_{i+1} | x_i, a_i = a] = P_g(g_i, g_{i+1})P_n(n_i, n_{i+1}, a) \quad (3)$$

where $P_g(g_i, g_{i+1})$ is the transition probability from channel state g_i to g_{i+1} and the node state transition probability $P_n(n_i, n_{i+1}, a)$ is given by

$$\begin{aligned} P_t(I, I, \cdot) &= (1 - q_a) \\ P_t(I, D_1, \cdot) &= q_a \\ P_t(D_i, D_{i+1}, 0) &= (1 - q_a), \quad i = 0, \dots, D-1 \\ P_t(D_D, I, 0) &= (1 - q_a) \\ P_t(D_i, D_0, \cdot) &= q_a, \quad i = 0, \dots, D \\ P_t(D_i, I, 1) &= (1 - q_a), \quad i = 1, \dots, D \end{aligned}$$

The strategies chosen by all mobile nodes determine the cost for each mobile node. Under the system states $\mathbf{x}^t = (x_1^t, x_2^t, \dots, x_N^t)$ and the control actions $\mathbf{a}^t = (a_1^t, a_2^t, \dots, a_N^t)$ of all the mobile nodes at time t , the cost for each mobile node is given by

$$e_i(\mathbf{x}^t, \mathbf{a}^t) = a_i^t \{ \max_{j, j \neq i} (a_j^t) + \delta [1 - \max_{j, j \neq i} (a_j^t)] P_f(g_i^t) \} E_c \quad (4)$$

where E_c is the energy consumption per frame. The weighting factor δ , ($0 \leq \delta \leq 1$), is used to indicate the relative importance of frame collision and channel frame error. $P_f(g_i)$ is the frame error rate when the channel state is g_i . Assuming independent bit errors, the frame error rate $P_f(g_i)$ for frame size L and the channel state g_i is given by

$$P_f(g_i) = 1 - (1 - P_b(g_i))^L \quad (5)$$

where $P_b(g_i)$ is obtained from (1).

To avoid wasting the energy consumption, the node can defer its transmission whenever possible with an acceptable buffer overflow. Given the state x_i^t and the taken action a_i^t , the buffer overflow of node i is given by

$$l_i^t(x_i^t, a_i^t) = \begin{cases} q_a, & n_i^t = D_k \text{ and } a_i^t = Defer \\ 1, & n_i^t = D_D \text{ and } a_i^t = Defer \\ 0, & \text{Otherwise} \end{cases} \quad (6)$$

where ($0 \leq k < D$).

Let $u_i(a_i, |x_i)$ denote the probability that the mobile node takes action a when it is in state x_i , β_i denote the probability distribution of initial state $x_i^{t=0}$. The expected average buffer overflow constraint can be defined as

$$L_{\beta_i, u_i}^i = \lim_{T \rightarrow \infty} \sup \frac{1}{T} \sum_{t=0}^{T-1} E_{\beta_i}^{u_i} \{ l_i^t(x^t, a^t) \} \leq L_{const}^i \quad (7)$$

We also define vectors $\mathbf{u} = (u_1, u_2, \dots, u_N)$ and $\beta = (\beta_1, \beta_2, \dots, \beta_N)$ as the set of strategies and initial state probability distributions, respectively, for all mobile nodes. The average cost per stage of each mobile node is defined as

$$E_{\beta, \mathbf{u}}^i = \lim_{T \rightarrow \infty} \sup \frac{1}{T} \sum_{t=0}^{T-1} E_{\beta}^{\mathbf{u}} \{ e_i(\mathbf{x}^t, \mathbf{a}^t) \} \quad (8)$$

The objective of each node is to find the optimal strategy u_i to minimize (8) subject to (7).

A. Linear Program

The set of all optimal responses for player i against a stationary policy u_{-i} can be obtained by using the Linear Program defined in [15].

LP(i:u): Find $z_i^* := \{z_i^*(x, a)\}_{x, a}$ where $(x, a) \in K_i$, that maximizes

$$\sum_{x \in X_i} \sum_{a \in A_i} E_i^u(x, a) z_i(x, a)$$

Subject to

$$\sum_{x \in X_i} \sum_{a \in A_i} [\delta_r(x) - P_{xar}^i] z_i(x, a) = 0, \forall r \in X_i$$

$$\sum_{x \in X_i} \sum_{a \in A_i} l_i(x, a) z_i(x, a) \leq L_{const}$$

$$z_i(x, a), \forall (x, a) \in K_i, \sum_{(x, a) \in K_i} z_i(x, a)$$

TABLE I. PARAMETER VALUES USED IN THE SIMULATIONS AND NUMERICAL RESULTS.

Parameters	Value (default)
Number of nodes	2
Doppler frequency (f_m)	10 Hz
Average SNR	10 dB
Frame size (including headers)	80 bytes
Control frame (Pilot/Response) size	8 bytes
Weighting factor in cost function (δ)	0.5

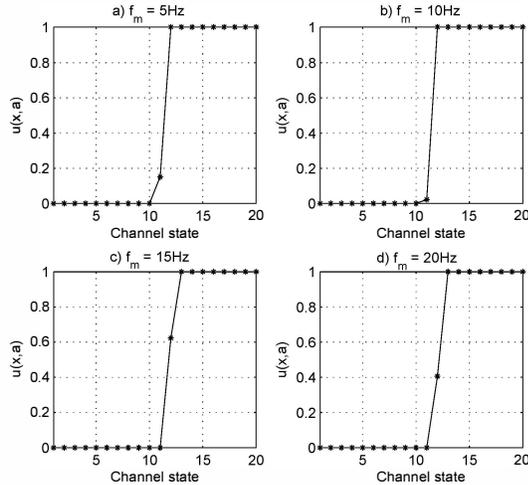


Fig. 3. The optimal threshold for the opportunistic transmission without delay constraint.

IV. NUMERICAL RESULTS

In this section, we analyze the characteristics of the OTS scheme and represent the opportunistic transmission scheme under various operating conditions. We perform various numerical experiments to investigate the characteristics of the OTS scheme. Table I summarizes the values of the various parameters used in our experiments.

Fig. 3 shows the impacts of varying channel on the optimum transmission threshold without delay constraints. As shown in Fig. 3, the channel states is partitioned in three state sets denoted by B, M, and G. Set B contains those states $0 \leq g_k < g_{Dth}$ in which the channel is bad and the transmission always defers. The SNR corresponding to g_{Dth} is the defer threshold. Set M include those states $g_{Dth} \leq g_k < g_{Tth}$ in which the node transmit packet with the optimal probability p^* and the SNR corresponding to g_{Dth} is g_{Tth} is an optimal transmission threshold. Fig. 4 shows the impacts of varying channel on the optimum transmission threshold with delay constraints. As the delay constraint (D) becomes more relaxed, the optimum transmission strategy converges to the deferring action, which leads to a higher transmission threshold. As shown in these figures, the defer threshold and transmission threshold becomes higher as channel varies higher or the delay becomes more insensitive. This observation is somewhat intuitive, since deferring the transmission to see a better channel is necessary to reduce the cost of transmission failure the fading channel varies rapidly.

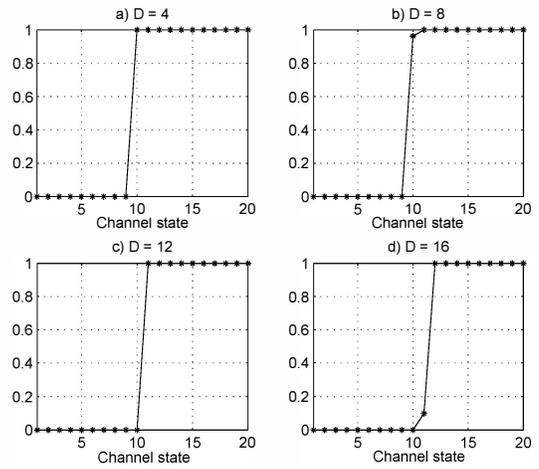


Fig. 4. The optimal threshold for the opportunistic transmission with delay constraint.

V. CONCLUSION

We exploited the constrained cost-coupled stochastic game to investigate the characteristics of OTS scheme, an opportunistic transmission strategy for wireless networks that operates under a time-varying wireless channel. We conducted extensive numerical experiments to observe and analyze the behavior of the OTS scheme over buffer overflow constraint in the context of delay sensitive applications. An optimum transmission policies is derived for OTS scheme in which the mobile node initiates transmission only when the channel quality exceeds the optimum threshold, so that unsuccessful transmissions causing a waste of energy are avoided whenever possible.

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