Multi-player Game Theoretic MAC Strategies for Energy Efficient Data Dissemination

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***Abstract*—The existence of multiple active sources in wireless data dissemination scenarios raises considerable channel access issues. Although the overall goal in the network is the successful accomplishment of the dissemination, the individual wireless nodes aim at maximizing their battery lifetime by minimizing their particular energy consumption. Considering thus the self-centered behavior of the nodes, we anticipate to design Medium Access Control (MAC) policies in order to provide the terminals with energy efficient solutions without compromising the dissemination completion time. In this paper, we propose non-cooperative game theoretic channel access strategies by estimating equilibrium points that achieve balance between conserving energy and completing the data dissemination. In particular, we present two different MAC strategies: i) a distributed approach for ad-hoc networks, and ii) a coordinated approach for infrastructure networks, where a central controller is sporadically used to accelerate the data dissemination. In addition, network-coded transmissions are considered to eliminate the need of control packets exchange. Both analytical and simulation results are provided to evaluate our proposed schemes, demonstrating the significant gains that game theoretic techniques can bring to the network performance compared to standardized solutions.**

***Index Terms*—Medium Access Control (MAC); Nash Equilibrium; Network Coding; Energy Efficiency.**

I. Introduction

The introduction of fourth generation (4G) technologies caused a shift from voice-centric applications to the mobile Internet, thus posing major challenges to the design of future communication systems. Recent reports have highlighted the importance of non-voice traffic in future wireless networks [1]. In particular, video and file sharing are increasingly dominating the mobile data traffic, and it is forecasted to account for more than 95% of total data traffic by 2015. This trend, along with the growth of peer-to-peer networking, have reinforced the need of distributing the digital information, such as video conferencing, live streaming, etc., among multiple end users. Hence, the concept of data dissemination has lately attracted great attention, especially in the context of wireless networks [2]-[4].

The problem of data dissemination becomes even harsher in wireless networks due to the energy constraints of battery operated mobile terminals. These limitations are just an additional component to the general issue of energy consumption, which has become a key factor for the design and implementation of "green"[1] networks, protocols and algorithms. Several works that deal with energy consumption issues in data dissemination scenarios have been proposed during the last few years [5]-[7]. Yilmaz *et al.* [5] proposed an innovative decentralized shortest hop multi-path algorithm for Wireless Sensor Networks (WSNs) in order to generate energy efficient paths for data dissemination. Their algorithm generates shortest hop braided multipath to be used for fault-tolerance or load-balancing, while guaranteeing low time and message complexity. Visvanathan *et al.* [6] introduced three hierarchical data dissemination schemes that prolong the lifetime of battery-driven sensor nodes by reducing the amount of information exchanged. The three proposed schemes create different hierarchical dissemination structures from the source to sink nodes in order to achieve reduced data redundancy and communication overhead. In the same context, Xing *et al.* [7] presented the Minimum Incremental Dissemination Tree, MIDT, to minimize the total energy consumption in data dissemination by jointly considering i) the quality of the links, ii) the power of all active radio modes (transmission, reception, idle), and iii) the data rates of different service requests. However, despite the reduction in the network's energy consumption, the aforementioned works either assume perfect coordination in MAC layer [5] or sacrifice the Quality of Service (QoS) by deteriorating the end-to-end delay [6],[7]. Therefore, a challenging task to overcome these limitations is the design of realistic energy efficient MAC protocols that respect the QoS constraints set by different applications in data dissemination scenarios.

The common global goal of all nodes in wireless data dissemination schemes is twofold: i) the completion of the dissemination in a reasonable time that satisfies the QoS restrictions, and ii) the least possible energy consumption that maximizes the nodes lifetime. However, in such scenarios, the selfish nature of the nodes may cause conflicting situations, since all nodes have revenue by the dissemination completion, but at the same time they aim at preserving their individual energy status. To this end, game theory has come into play to study mathematical models of conflict and cooperation between intelligent rational decision-makers [8]. In particular, during the last decade, game theoretic frameworks have been broadly proposed to investigate and model the medium access contention problem in wireless networks. The vast majority of these works focus on estimating the Nash Equilibrium (*NE*) [9] point of a given game, which can be defined as a steady-state condition that corresponds to the mutual best response

[1] "Green" refers to all environment-aware techniques.

of all players. Hence, a strategy combination achieves the *NE* if no player can improve her utility by unilaterally deviating from her own strategy.

MacKenzie and Wicker [10] proposed a pioneer game theoretic model to study the behavior of selfish nodes in slotted Aloha systems. In [11], the same authors extended their former work by proving the existence of equilibria in multi-packet reception models. Altman *et al.* [12] introduced a non-cooperative game, where Aloha nodes aim at maximizing their throughput under non-saturation conditions. Inaltekin and Wicker [13] analyzed the asymmetric *NE* for heterogeneous networks, where nodes are non-identical, having different perceived utilities. More recently, Cho *et al.* [14] proposed robust random-access protocols for wireless networks in fading environments, where the terminal nodes estimate the *NE* of a random-access game. Their game formulation provides the nodes with better channel states with higher access probabilities, thus guaranteeing the multiuser diversity. In the same context, Wang *et al.* [15] introduced a game theoretic model in order to design a *NE* threshold associated to the statistical channel characteristics.

Several game theoretic works have been also conducted regarding the IEEE 802.11 Distributed Coordination Function (DCF) ([16]-[18]). In [16], Fang and Bensaou dealt with the problem of fair bandwidth sharing among the wireless nodes in ad-hoc networks. They proposed two different game formulations for the specific problem, where the solutions are provided without the need for global knowledge. Zhao *et al.* [17] presented an incompletely cooperative game to enhance the performance of MAC protocols in wireless mesh networks. In their game, the nodes first estimate the number of competing stations, and they adapt their individual equilibrium strategies by adjusting their local contention parameters, i.e., the minimum contention window. Tinnirello *et al.* [18] proposed a game theoretic analysis of persistent access schemes for wireless infrastructure networks, where the nodes are interested in both upload and download traffic. The authors proved the existence of *NE*, while they used the access point as an arbitrator to improve the global network performance.

Despite their novel insights on MAC protocol design, the above stated game theoretic works have been proposed mainly for conventional networks where the nodes aim at maximizing their individual revenue, primarily in terms of achieved throughput. However, as already mentioned, recent studies have indicated the rising evolution of data dissemination in modern telecommunications networks, thus stressing the need for designing new MAC protocols that consider the conflicting selfish interests of the nodes along with the content sharing which constitutes their common goal. In addition, new metrics have to be envisaged for data dissemination scenarios in order to guarantee the on-time content delivery as well as the battery autonomy of the mobile devices.

In this context, this paper introduces multi-player game theoretic channel access strategies for wireless data dissemination schemes, where multiple source nodes have conflicting interests. We propose non-cooperative strategic game formulations, where each player[2] identifies a steady state condition (*NE*) in order to balance a tradeoff between the energy saving and the data dissemination completion. The contribution of our work is twofold:

1) Taking into account the energy efficiency importance in wireless communications, we present two different game theoretic MAC strategies: i) a distributed approach for infrastructure-less ad-hoc networks where the wireless nodes individually estimate the *NE* transmission probabilities according to energy-based utility functions, and ii) a coordinated approach for infrastructure networks, where the nodes also act individually to achieve the *NE*, while a central controller is occasionally used to facilitate the dissemination procedure. The proposed game formulations can be applied to realistic wireless networks, where multiple sources compete for channel access.
2) We present an analytical probabilistic framework to evaluate the network performance in terms of energy efficiency and completion time in the *NE* state. The proposed analytical model further demonstrates the scalability of both approaches, while proving that our game theoretic strategies outperform other standardized solutions.

The remainder of this paper is organized as follows. Section II presents our system model. In Section III, we introduce our multi-player game theoretic approaches for energy efficient data dissemination. Section IV presents the analytical model for the completion time and energy efficiency performance of the proposed schemes. The validation of the model along with numerical results are provided in Section V. Finally, Section VI concludes the paper.

II. System Model

Our network, depicted in Fig. 1, consists of: i) a Base Station (BS) that initially broadcasts the digital information, ii) a set of n nodes (so-called *source* nodes) located inside the transmission range of the BS, and iii) a set of l nodes (so-called *sink* nodes) placed outside the transmission range of the BS, but inside the transmission range of at least one *source* node. Moreover, in our system the *source* nodes have the same impact[3] on the network, affecting the same number ($J \in [0, l]$) of *sink* nodes. The data dissemination is carried out in two phases: During the first phase, the BS transmits the information to the n *source* nodes in its coverage area, while in the second phase, the *source* nodes disseminate the data to the rest l sink nodes. It is worth mentioning that our proposal can be adaptively employed in large-scale networks, by considering a layered architecture consisting of distinct phases, where the *sink* nodes of each phase constitute the *source* nodes of the following phase. This is, though, out of the scope of the present work.

Our study is particularly focused on the second phase of the dissemination, where we assume that the source nodes have already received the disseminated content by the BS,

[2] Please note that the terms "player" and "node" are used interchangeably in this paper.

[3] Impact is defined as the number of sink nodes that benefit from one transmission [19].

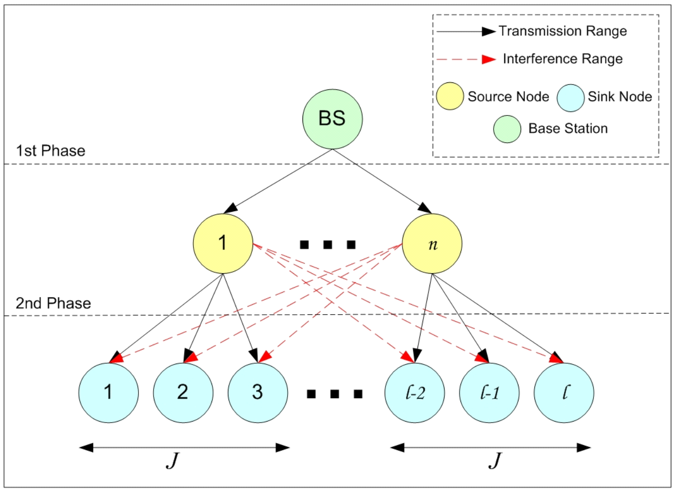

Fig. 1. System Model

thus having packets to send in their buffers (i.e., the network operates in saturated conditions). We further adopt a slotted system where the node with the greatest impact on the network gains the channel access to transmit in every slot, since this technique has been recently proven to expedite the dissemination procedure [19]. However, the mutual interference among the transmitting radio signals allows for only one transmission in every slot, thus hindering the realization of multiple parallel transmissions. Hence, the implementation of a MAC mechanism is essential to coordinate the transmissions of many source nodes in the network.

Regarding the energy aspect of the problem, we denote by $\mathcal{E}_{TOTAL}$ the initial energy available to each source node. Furthermore, since our study examines the second phase of the dissemination, where the sources have already received the content, we consider two particular energy costs for the wireless interface, i.e., $\mathcal{E}_T$ and $\mathcal{E}_W$, which correspond to the energy consumption during the transmission and the idle mode, respectively.

In our scheme, random linear network coding techniques are used to assist the progress of the dissemination. Specifically, since data collection is an equivalent situation to the coupon collector's problem [20], network coding can significantly simplify the complexity of the solution [21]. In particular, the transmission of packet linear combinations instead of just forwarding the information flows eliminates the necessity of exchanging acknowledgement (ACK) packets. Hence, it is sufficient for a network node to receive enough linearly independent combinations in order to decode the entire data set. On the other hand, network coding comes with an additional cost, since the data packets are charged with an extra overhead due to the network coding header (NC_H). The specific header contains essential information for the decoding process, such as the coding vector, the generation size and the generation index [22].

III. Multi-player Game Theoretic Channel Access Strategies for Wireless Data Dissemination

In this section, we present our game formulation along with the two proposed MAC strategies.

A. Game Formulation

In our scenario, the global goal of all nodes is the successful completion of the data dissemination. However, the sender's role implies energy wasting, hence particular incentives should be provided to a particular player in order to take up this role. On the other hand, if no one transmits, the nodes will waste all their energy in idle state, thus hindering the data dissemination. To analyze this conflicting situation, we model the access scenario as a *static non-cooperative game with complete information* [8], where each player selects the strategy that maximizes her own utility.

In game theory, a game Γ is represented by a tuple $\Gamma = (\mathcal{N}, (\mathcal{A}_i)_{i\in\mathcal{N}}, (U_i)_{i\in\mathcal{N}})$, where $\mathcal{N} = \{1, ..., n\}$ is the set of players. For each player $i \in \mathcal{N}$, $\mathcal{A}_i$ is a finite set of actions, while U_i is a *utility* (or *payoff*) function, given a set of actions. Our game consists of n players (*source* nodes) who decide if they transmit or not in each slot. Therefore, we use the following notations to be compatible with the game theory rules: $\mathcal{N} = \{1, ..., n\}$ and $\mathcal{A}_i = \{Transmit(T), Wait(W)\}$. Furthermore, in order to focus on the energy aspect of the problem, the utility function has been chosen such that to quantify the lifetime of the nodes. Defining $\mathcal{E}_{TOTAL}$ as the total energy amount available to each node and $\mathbf{E}[\mathcal{E}_i]$ as the average amount of energy consumed by the node's i wireless interface in each slot, the utility function of player i is given by:

$$U_i = \frac{\mathcal{E}_{TOTAL}}{\mathbf{E}[\mathcal{E}_i]}. \tag{1}$$

The strategic form of the proposed game is presented in Table I. The peer-to-peer nature and the symmetry of the problem have allowed us to formulate it as an n-player game, considering 2 macro-players: Player 1 represents node i, while Player 2 includes the rest $n-1$ nodes except for node i. The table's contents correspond to the Player's 1 energy costs with regard to the different contingencies in Player's 2 set. In particular, the values $\mathcal{E}_T$ and $\mathcal{E}_W$ represent the energy amounts spent during transmission and idle mode, respectively, while $\mathcal{E}_C$ corresponds to the cost in case that the dissemination does not proceed either due to collisions or idle slots. For the sake of clarity and without loss of generality, we assume that $\mathcal{E}_W = a \cdot \mathcal{E}_T$ and $\mathcal{E}_C = b \cdot \mathcal{E}_T$, where a depends on the ratio of the transmit and idle power, while b defines the impact of collisions and idle slots in the system. It is also worth noting that, although $\mathcal{E}_C$ does not denote an actual energy consumption, it is of fundamental importance in our game formulation, since it indicates a long-term cost for the nodes, in the case that the dissemination is not completed. In the following sections, we study the impact of parameter b on the outcome of the proposed game.

Given the system model, five possible outcomes derive by Table I for each slot. Two of them result in successful

TABLE I
GAME FORMULATION FOR THE ENERGY COSTS OF PLAYER 1

		Player 2 (all the other n-1 nodes)		
		T		**W**
Player 1 (node i)	**T**	$\mathcal{E}_T+\mathcal{E}_C$		$\mathcal{E}_T$
	W	*Successful Transmission*	*Failed Transmission*	$\mathcal{E}_W+\mathcal{E}_C$
		$\mathcal{E}_W$	$\mathcal{E}_W+\mathcal{E}_C$	

transmissions, while the rest three lead to unsuccessful/failed slots, either idle or collided. In particular:

$s1$) Player 1 transmits - All nodes in Player 2 wait: Successful transmission.

$s2$) Player 1 waits - Exactly one node of Player 2 transmits: Successful transmission.

$f1$) Player 1 transmits - At least one node of Player 2 transmits: Collision.

$f2$) Player 1 waits - At least two nodes of Player 2 transmit: Collision.

$f3$) Player 1 waits - All nodes in Player 2 wait: Idle slot.

The formulation of our problem in a strategic form reveals n *NE* in pure strategies. These *NE*, which are usually common in medium access games [13], correspond to the successful transmissions in the system, i.e., the case of only one node transmitting. However, the unfairness of pure strategies *NE* [23], along with the requirement for central coordination to achieve a collision-free network have motivated us to study the problem in the mixed strategies domain, in order to provide feasible and applicable solutions for distributed systems. In the following sections we introduce our game theoretic medium access policies: i) a distributed approach where the wireless nodes individually estimate the *NE* channel access probabilities according to the adopted energy-based utility function, and ii) a coordinated approach for infrastructure networks, where the nodes act individually to achieve the *NE*, while a central controller is occasionally used to facilitate the dissemination procedure.

B. Distributed Access Strategy

In the distributed access strategy, the nodes calculate their transmission probabilities in a totally decentralized manner. In particular, each node (Player 1) selects a transmission probability, s_i, having as an upper goal to estimate the value of this probability that maximizes its payoff. In addition, the symmetry of the game due to the peer nature of the nodes and their identical characteristics offers two important advantages. First, all $n-1$ nodes of Player 2 can be grouped assuming a common transmission probability s_j. The second important fact is that, eventually, the values of the probabilities s_i and s_j should be identical, as derives by the symmetric *NE* properties.

Considering the energy costs in the strategic form of the proposed game (Table I), the expected energy consumption for node i, $\forall i \in \mathcal{N}$ is given by:

$$\mathbf{E}[\mathcal{E}_i] = p_{s1}\cdot\mathcal{E}_T+p_{s2}\cdot\mathcal{E}_W+p_{f1}\cdot(\mathcal{E}_T+\mathcal{E}_C)+p_{f2}\cdot(\mathcal{E}_W+\mathcal{E}_C)+p_{f3}\cdot(\mathcal{E}_W+\mathcal{E}_C) \quad (2)$$

where the probabilities p_{s1}, p_{s2}, p_{f1}, p_{f2} and p_{f3} correspond to the five potential contingencies of each slot and can be mathematically expressed as[4]:

$$p_{s1} = s_i\cdot(\bar{s}_j)^{n-1}, \forall i,j\in\mathcal{N}, n\in\mathbb{Z}, n\geq 2 \quad (3)$$

$$p_{s2} = \bar{s}_i\cdot(n-1)\cdot s_j\cdot(\bar{s}_j)^{n-2}, \forall i,j\in\mathcal{N}, n\in\mathbb{Z}, n\geq 2 \quad (4)$$

$$p_{f1} = s_i\cdot(1-(\bar{s}_j)^{n-1}), \forall i,j\in\mathcal{N}, n\in\mathbb{Z}, n\geq 2 \quad (5)$$

$$p_{f2} = \bar{s}_i\cdot((1-(1-s_j)^{n-1})-(n-1)\cdot s_j\cdot(\bar{s}_j)^{n-2}), \forall i,j\in\mathcal{N}, n\in\mathbb{Z}, n\geq 2 \quad (6)$$

$$p_{f3} = \bar{s}_i\cdot(\bar{s}_j)^{n-1}, \forall i,j\in\mathcal{N}, n\in\mathbb{Z}, n\geq 2 \quad (7)$$

In this point, it has to be emphasized that each source node participates in the game from Player's 1 perspective and the first goal is the selection of a strategy that maximizes her perceived payoff. To that end, the best response of s_i to the strategy s_j is given by setting $\frac{\partial U_i}{\partial s_i}=0$. The partial derivative of the utility function $U_i=\frac{\mathcal{E}_{TOTAL}}{\mathbf{E}[\mathcal{E}_i]}$ with respect to s_i, is equal to:

$$\frac{\partial U_i}{\partial s_i} = -\frac{\mathcal{E}_{TOTAL}}{(\mathbf{E}[\mathcal{E}_i])^2}\cdot\frac{\partial(\mathbf{E}[\mathcal{E}_i])}{\partial s_i}. \quad (8)$$

Hence, as derived by Eq. (8), in order to estimate the best response for the particular game, it is sufficient to solve the equation:

$$\frac{\partial(\mathbf{E}[\mathcal{E}_i])}{\partial s_i} = 0. \quad (9)$$

Let us recall that $\mathcal{E}_W = a\cdot\mathcal{E}_T$ and $\mathcal{E}_C = b\cdot\mathcal{E}_T$. Differentiating Eq. (9) with respect to s_i yields:

$$a\cdot(s_j-1)\cdot(\bar{s_j}^n-s_j+1)+b\cdot(n\cdot s_j+s_j-2)\cdot\bar{s_j}^n+(s_j-1)^2=0. \quad (10)$$

Apparently, the number of source nodes (n) in the network is the only required information for the estimation of s_j, which maximizes the utility function. This information can be provided by the upper OSI layers (e.g., network layer) through the routing tables or the Management Information Base (MIB). However, the context-awareness is currently an active research topic [24] and it is expected that, during the next few years, such kind of information will be available to all nodes in decentralized systems.

Exploiting the symmetry of the game, in Section III-D, we prove that the estimated value for the s_j turns out to be the *NE*, while we also provide practical numerical examples for different scenarios.

C. Coordinated Access Strategy

In data dissemination scenarios, the delay metric constitutes a key QoS indicator, as well as a restrictive factor for the network performance. The application of the proposed game theoretic distributed channel access scheme to the system potentially causes unsuccessful or empty slots in the network, either due to collisions or idle slots when the nodes mutually transmit or wait, respectively. Hence, in order to bound the time needed to complete the data dissemination, we propose a variation of the distributed access strategy, so-called game theoretic coordinated channel access strategy, applicable in infrastructure networks.

In particular, in the coordinated approach we adopt the use of a central controller that deterministically provides the

[4] We use the notation $\bar{s}_i$ to denote the complementary probability of s_i, i.e., $\bar{s}_i = 1-s_i$.

source nodes with channel access in case of k_f consecutive unsuccessful slots. More specifically, the controller is able to distinguish between idle slots, successful transmissions and collisions by sensing the energy level in the channel [25] and, accordingly, to select the node to transmit in case of k_f successive failed slots in the network. It is worth noting that unlike pure centralized systems where the central controller schedules the total transmissions, in our proposed strategy the controller intervenes only occasionally by polling one station, hence reducing the control packet overhead and preserving valuable energy. Although out of the scope of our work, the optimal selection of k_f constitutes a challenging research problem and its study would reveal intriguing tradeoffs for different topologies and scenarios. For instance, small values of k_f would lead in frequent polling, while big values of k_f imply higher degree of decentralization. In Section V-B, we provide some interesting insights with regard to the performance of our strategies compared to wholly centralized approaches.

In our work, we examine a particular case study of $k_f = 2$ in order to investigate the changes that the existence of a central controller can bring in the game formulation and, consequently, in the protocol design. Hence, considering $k_f = 2$ and given the operation of the game theoretic coordinated medium access strategy, there are three possible cases before the controller's intervention:

i) 1^{st} slot: either successful or unsuccessful transmission.
ii) 2^{nd} slot: unsuccessful transmission in the first slot followed by either successful or unsuccessful transmission.
iii) 3^{rd} slot: unsuccessful transmissions in the first two slots and the central controller defines which node is going to transmit.

For the sake of clarity and comprehension, let us denote by Z the expected energy consumption ($\mathbf{E}[\mathcal{E}_i]$) of a node in the first slot, as denoted in Eq. (2). Therefore, the expected energy $\mathbf{E}[\mathcal{E}_i']$ of node i in the coordinated scheme is given by:

$$\mathbf{E}[\mathcal{E}_i'] = [Z] + [(p_{f1} + p_{f2} + p_{f3}) \cdot Z] + [(p_{f1}^2 + p_{f2}^2 + p_{f3}^2 + \\ + 2 \cdot p_{f1} \cdot p_{f2} + 2 \cdot p_{f1} \cdot p_{f3} + 2 \cdot p_{f2} \cdot p_{f3}) \cdot p_{poll} \cdot \mathcal{E}_T] \tag{11}$$

where the three terms in brackets correspond to the expected values of energy consumption with regard to the three aforementioned possible cases, respectively. Furthermore, the probabilities p_{s1}, p_{s2}, p_{f1}, p_{f2} and p_{f3} have been defined in Section III-B, while the probability p_{poll} is considered constant, due to the scheduler's fairness.

To distinguish from the distributed access strategy, let us denote by $U_i' = \frac{\mathcal{E}_{TOTAL}}{\mathbf{E}[\mathcal{E}_i']}$ the utility function of the coordinated policy. Accordingly, the best response of s_i is given by setting $\frac{\partial U_i'}{\partial s_i} = 0$ or equivalently $\frac{\partial(\mathbf{E}[\mathcal{E}_i'])}{\partial s_i} = 0$. Therefore, we end up in Eq. (12) at the top of the next page, where, unlike the distributed strategy, the best response depends on both s_i and s_j. In the next section we will explicitly study how we can derive the *NE* probabilities for both strategies, providing also practical numerical solutions for particular case studies.

D. NE Characterization and Numerical Results

Subsections III-B and III-C were dedicated to the theoretical analysis of the best response estimation under different medium access strategies. The present subsection provides complete *NE* characterizations and practical numerical results for various scenarios and parameters.

a) Distributed Game: Several formal definitions for the *NE* characterization have been proposed in the literature, since the introduction of the pioneer work of Nash [9]. One of the most widely-adopted definitions is the following [28]:

A mixed-strategy profile $\mathbf{s}^*$ *is a mixed-strategy NE if, for each player* $i \in \mathcal{N}$*, we have:*

$$U_i(s_i^*, \mathbf{s}_{-i}^*) \geq U_i(s_i, \mathbf{s}_{-i}^*), \forall i \in \mathcal{N}. \tag{15}$$

Therefore, we are looking for a strategy s_i^* that maximizes the utility of player i in the network. Unlike other related works [18] that propose best response dynamics, which eventually converge to a *NE*, in our case, the symmetry of the problem enables us to derive one-shot symmetric *NE* strategies. Let us recall that each source node in the network participates in the game by studying it from Player's 1 perspective. Hence, the solution of Eq. (9) corresponds to the strategy that maximizes the individual payoffs of all sources. As a result, this symmetric strategy can be considered as the mutual best response of all players and, consequently, the *NE* of the game, since no player has any incentives to unilaterally deviate. Taking into account that Eq. (10) is formally the same for all nodes, it can be concluded that $s_i = s_j = s^*$ and the *NE* transmission probability s^* can be calculated by solving:

$$a \cdot (s^* - 1) \cdot (\bar{s^*}^n - s^* + 1) + b \cdot (n \cdot s^* + s^* - 2) \cdot \bar{s^*}^n + (s^* - 1)^2 = 0. \tag{16}$$

Let us recall that the solutions that correspond to pure actions (i.e., $s^* = 0$ and $s^* = 1$) have been excluded from the set of potential strategies due to the need for central coordination. Considering as a use case the IEEE 802.11g Standard [26], where the power level of the reception (P_R) and idle state (P_I) is the 70% of the transmission power (P_T) [27], we set $a = 0.7$. Regarding b, which is the weight factor of the energy cost in case that the dissemination does not proceed, we assume three different values ($b = 0.8$, $b = 1.0$ and $b = 1.2$), with respect to the impact that the standstill of the dissemination causes on the network. To this end, the *NE* transmission probabilities for different number of players (source nodes) in the network are presented in Table II, where we observe that the *NE* transmission probability increases with b, as the nodes adopt an "aggressive" attitude to complete the process. Conversely, for fixed values of b, the transmission probability decreases as the number of competing source nodes increases in the network. It is worth noting that the *NE* in our game are unique [9], facilitating the real implementation of our strategies.

The main advantage of the *NE* is the achievement of a balance in the system. However, despite its popularity, the *NE* does not always reach the ideal state for a system, known as "Pareto efficient" state. To determine the optimal strategy in our problem, we substitute $s_i = s_j = s$ in the utility function. Figure 2 depicts the variation of the utility using identical strategies, assuming $a = 0.7$, $b = 1.0$ and a various number of source nodes. In this figure, it can be observed that *NE* transmission probabilities result in high utility values, but

$$
\begin{aligned}
&-ac(n-1)s_j\bar{s}_j^{n-2} - (a+b)c\bar{s}_j^{n-1} + c\bar{s}_j^{n-1} + 2c\bar{s}_i(1-\bar{s}_j^{n-1})\bar{s}_j^{n-1} - 2cs_i(1-\bar{s}_j^{n-1})\bar{s}_j^{n-1} - 4c\bar{s}_i(1-(n-1)\bar{s}_j^{n-2}s_j)\bar{s}_j^{n-1}+\\
&2c\bar{s}_i(1-\bar{s}_j^{n-1})(1-(n-1)\bar{s}_j^{n-2}s_j) + (b+1)c(1-\bar{s}_j^{n-1}) - 2c\bar{s}_i\bar{s}_j^{2n-2} - (a+b)c(1-(n-1)\bar{s}_j^{n-2}s_j) + 2cs_i(1-\bar{s}_j^{n-1})^2+\\
&2c\bar{s}_i(1-(n-1)\bar{s}_j^{n-2}s_j)^2 - 2cs_i(1-\bar{s}_j^{n-1})(1-(n-1)\bar{s}_j^{n-2}s_j) + s_i(1-\bar{s}_j^{n-1})g(s_j) - (1-(n-1)\bar{s}_j^{n-2}s_j)f(s_i,s_j) - f(s_i,s_j)\bar{s}_j^{n-1}-\\
&\bar{s}_i(1-(n-1)\bar{s}_j^{n-2}s_j)g(s_j) + (1-\bar{s}_j^{n-1})f(s_i,s_j) + \bar{s}_i g(s_j)\bar{s}_j^{n-1} = 0
\end{aligned} \tag{12}
$$

where

$$f(s_i,s_j) = ac(n-1)\bar{s}_i s_j\bar{s}_j^{n-2} + (a+b)c\bar{s}_i\bar{s}_j^{n-1} + cs_i\bar{s}_j^{n-1} + (b+1)cs_i(1-\bar{s}_j^{n-1}) + (a+b)c\bar{s}_i(1-(n-1)\bar{s}_j^{n-2}s_j) \tag{13}$$

and

$$g(s_j) = -ac(n-1)s_j\bar{s}_j^{n-2} - (a+b)c\bar{s}_j^{n-1} + c\bar{s}_j^{n-1} + (b+1)c(1-\bar{s}_j^{n-1}) - (a+b)c(1-(n-1)\bar{s}_j^{n-2}s_j) \tag{14}$$

TABLE II
NE TRANSMISSION PROBABILITIES

	Distributed			Coordinated		
n	$s^*(b=0.8)$	$s^*(b=1.0)$	$s^*(b=1.2)$	$s^*(b=0.8)$	$s^*(b=1.0)$	$s^*(b=1.2)$
2	0.312	0.350	0.375	0.423	0.432	0.439
3	0.180	0.207	0.225	0.259	0.268	0.275
4	0.127	0.147	0.161	0.185	0.193	0.199
5	0.097	0.113	0.125	0.144	0.150	0.156
6	0.080	0.092	0.102	0.117	0.123	0.128
7	0.067	0.078	0.086	0.099	0.104	0.108
15	0.030	0.035	0.038	0.044	0.046	0.048
17	0.026	0.030	0.034	0.039	0.041	0.043
19	0.023	0.027	0.030	0.034	0.036	0.038

not the optimal ones, thus proving the Pareto inefficiency of the *NE*, which is a common phenomenon in non-cooperative games. In addition, it is worth noticing how the tendencies of the plots vary for different number of nodes. In particular, the presence of numerous nodes in the network restricts the range of high payoff probabilities, thus requiring the precise calculation of the *NE* in order to avoid undesirable low utility situations. However, our proposed game theoretic formulation deals effectively with these issues by estimating accurate, close to optimal channel access probabilities.

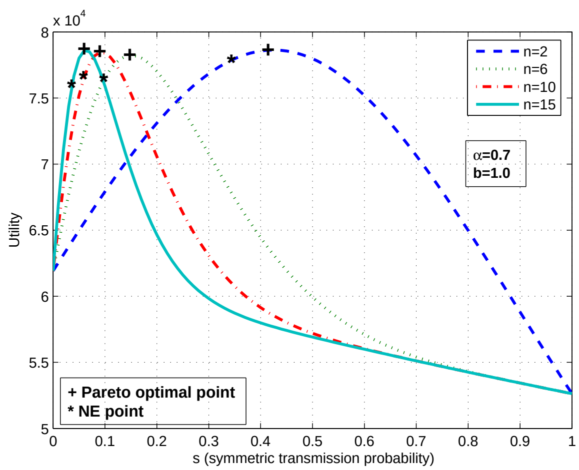

Fig. 2. Utility vs. Symmetric Strategies

b) Coordinated Game: In the coordinated approach, the best response equation (i.e., Eq. (12)) depends on both s_i and s_j. Hence, in order to characterize the *NE* in this case, we have to slightly differentiate and, thus, we adopt the following common definition as derived by the fixed point theorem [29]:

The definition of the NE as the mutual best response implies that any fixed point in mixed strategies constitutes a NE for the game.

As derives by Eq. (12), the probability s_j can be expressed as a function of s_i, i.e., $s_j = \varphi(s_i)$. Consequently, the fixed point solutions in the best response of s_i to s_j would characterize the symmetric NE of the game. The system of equations can be formulated as:

$$
\begin{aligned}
s_j &= \varphi(s_i)\\
s_j &= s_i
\end{aligned} \tag{17}
$$

The solutions to the above system, known as fixed point solutions, are the points that satisfy the equation $s_i = \varphi(s_i)$. To this end, Fig. 3 plots the results of Eq. (17) for various numbers of source nodes (n) in the particular case of $a = 0.7$ and $b = 1.0$. In this plot, it can be observed that for every n there is only one fixed-point solution in the strategy space ($s_i, s_j \in [0, 1]$), which is the unique equilibrium of the game according to the *NE* definition.

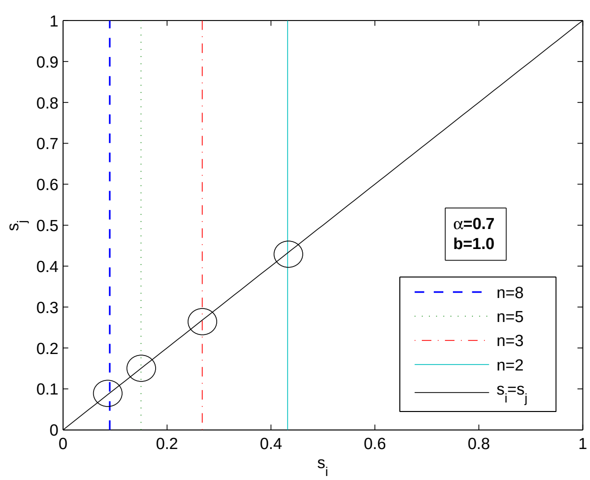

Fig. 3. s_i vs. s_j and Fixed Point solutions for various number of source nodes in the network

More detailed results for different values of b are included in Table II, where we can see that the estimated values of *NE* under the coordinated access strategy are higher compared to the *NE* probabilities in the distributed strategy, under the same conditions and variables. This trend can be rationally justified by the presence of the central controller that acts as a safeguard to guarantee correct transmission after consecutive unsuccessful slots. Hence, the nodes are enabled to estimate higher transmission probabilities without taking into account the threat of collisions.

IV. Performance Analysis

Until now, we have presented two different versions of the proposed game: i) a distributed and ii) a coordinated access strategy. In this section we analytically estimate the data dissemination completion time and the energy efficiency performance of both schemes.

A. Completion Time

Although the data dissemination in our system model takes place in two phases, we focus our analysis in the latter phase, where our game theoretic access techniques are applied. Therefore, the total completion time is represented by:

$$\mathbf{E}[T_{total}] = \mathbf{E}[R] \cdot (p_s \cdot T_{tr} + p_i \cdot \sigma + p_c \cdot T_c) \tag{18}$$

where $\mathbf{E}[R]$ is the average number of slots needed in order for the data dissemination to be accomplished. The probabilities of having a successful transmission, an idle slot or a collision are given by p_s, p_i and p_c, respectively. Moreover, the terms T_{tr}, σ and T_c represent the duration of a transmission, an empty slot and a collision, respectively. The slot time σ is a system parameter, while T_{tr} depends on the packet length and the transmission data rate. Furthermore, we consider that $T_c = T_{tr}$, since the collision detection takes place on the receiver's side.

The term $\mathbf{E}[R]$ can be further analyzed as

$$\mathbf{E}[R] = \frac{R_{ideal}}{p_s}, \tag{19}$$

where R_{ideal} is the minimum number of slots in case of ideal scheduling among the nodes, i.e., contention-free scheme. As it has been already demonstrated in [19], it can be written as

$$R_{ideal} = M \cdot \left\lceil \frac{l}{J} \right\rceil, \tag{20}$$

where M is the number of the information data packets, l is the number of the sink nodes, and J represents the impact of the source nodes on the network, i.e., the number of sink nodes that a source node affects.

Therefore, the most challenging part is to derive closed-form formulas for the probabilities of successful transmissions (p_s), idle slots (p_i) and collisions (p_c) in our proposed access strategies. In the following subsections, we compute the theoretical values of p_s, p_i and p_c for both the distributed and the coordinated access scheme.

1) Distributed Access Scheme: Given that, in the distributed access scheme, the source nodes estimate a common transmission probability s^* according to the *NE* of the game, we are able to derive closed-form formulas for the probabilities p_s, p_i and p_c. The probability that at least one of the n sources attempts to transmit in a given slot can be expressed as $p_{tr} = 1 - (1 - s^*)^n$, while the probability of a successful transmission, i.e., one station transmits conditioned on the fact that at least one station transmits, is given by:

$$p_{s|tr} = \frac{n \cdot s^* \cdot (1 - s^*)^{n-1}}{1 - (1 - s^*)^n} \tag{21}$$

Therefore, the probabilities of having a successful (p_s), collided (p_c) or idle (p_i) slot can be written as:

$$p_s = p_{tr} \cdot p_{s|tr} \tag{22}$$

$$p_c = p_{tr} \cdot (1 - p_{s|tr}) \tag{23}$$

$$p_i = 1 - p_{tr} \tag{24}$$

Hence, combining the equations (18) - (24), we are able to estimate the completion time for the dissemination under the distributed access policy.

2) Coordinated Access Scheme: The analytical model of the coordinated access scheme is modified due to the presence of the central controller. Let us recall that, under this scheme, the central controller schedules a transmission after two consecutive unsuccessful (idle or collided) slots in the network. Therefore, in order to model our strategy, we consider a Bayesian Network of three states - x, y, z - where the outcomes of states x and y determine the outcome of state z. Figure 4 depicts the associate probabilities to our game, where the probabilities p_s, p_c and p_i have been defined, and the term p_f denotes the probability of having a failed (either idle or collided) slot. Moreover, we use the notations c_i and $\bar{c}_i$ to denote that a transmission in the i^{th} slot is successful or unsuccessful, respectively. One transmission is considered successful if exactly one node is transmitting in the specific slot. For our particular game, we can write:

$$p(c_i) = p_s = p_{tr} \cdot p_{s|tr}, \forall i \in \mathbb{N} \tag{25}$$

$$p(\bar{c}_i) = 1 - p(c_i), \forall i \in \mathbb{N} \tag{26}$$

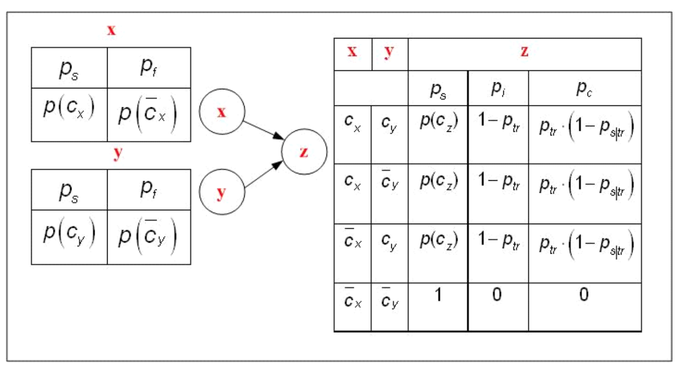

Fig. 4. Bayesian Network of the proposed strategy

Since the success in one random slot depends on the status of the two previous slots, we use conditional probabilities to estimate the probabilities, p_s, p_i and p_c. Specifically, p_s can be calculated as:

$$p_s = \sum p(x, y, z = c_z), \forall x \in \{c_x, \bar{c}_x\}, y \in \{c_y, \bar{c}_y\} \tag{27}$$

The statistical independence of the events enables us to use the definition of conditional probability in order to simplify the above formula. Thus, we have:

$$p_s = \sum p(z = c_z|x, y) \cdot p(x) \cdot p(y), \forall x \in \{c_x, \bar{c}_x\}, y \in \{c_y, \bar{c}_y\} \quad (28)$$

Accordingly, we can calculate the probability of having an idle slot or a collision as:

$$p_i = \sum p(z = idle|x, y) \cdot p(x) \cdot p(y), \forall x \in \{c_x, \bar{c}_x\}, y \in \{c_y, \bar{c}_y\} \quad (29)$$

$$p_c = \sum p(z = col|x, y) \cdot p(x) \cdot p(y), \forall x \in \{c_x, \bar{c}_x\}, y \in \{c_y, \bar{c}_y\} \quad (30)$$

In the above equations, the probabilities $p(x)$ and $p(y)$ can be derived by the formulas (25) and (26), while the conditional probabilities can be found in Fig. 4. Specifically, when there is at least one successful transmission in the previous two slots, the probability of having a successful transmission p_s in the current slot is independent of the history, equal to $p(c_z)$. On the other hand, if the last two slots were unsuccessful (either idle or collided), the probability p_s on the current slot is equal to one, since the controller schedules the transmission. Consequently, the probabilities of having idle slot or collision are both equal to zero.

Therefore, we have derived closed-form formulas for the completion time of the two proposed medium access games for data dissemination.

B. Energy Efficiency

The detailed analysis for the operation of our proposed game theoretic policies enables us to derive a closed-form expression to describe the energy efficiency in the network during the second phase of the dissemination:

$$\eta = \frac{D}{\mathbf{E}[\mathcal{E}_{total}]} \quad (31)$$

where D denotes the useful data delivered during the second phase of the dissemination, calculated as $D = M \cdot Payload \cdot l$, with $Payload$ corresponding to packet payload, while M and l have been defined in subsection IV-A. On the other hand, the term $\mathbf{E}[\mathcal{E}_{total}]$ denotes the expected lower bound for the energy consumption in the radio part of the network, estimated as:

$$\mathbf{E}[\mathcal{E}_{total}] = \mathbf{E}[R] \cdot (\mathbf{E}[\mathcal{E}_{succ}] + \mathbf{E}[\mathcal{E}_{idle}] + \mathbf{E}[\mathcal{E}_{col}]) \quad (32)$$

where $\mathbf{E}[R]$ was defined in Section IV-A, while the terms $\mathbf{E}[\mathcal{E}_{succ}]$, $\mathbf{E}[\mathcal{E}_{idle}]$ and $\mathbf{E}[\mathcal{E}_{col}]$ correspond to the expected energy consumption during the successful transmissions, the idle slots and the collision periods, respectively. To compute these values, we consider three different modes for the wireless interface of each node:

1) **Transmission mode**, when the node is transmitting data packets.
2) **Reception mode**, when the node is receiving data packets.
3) **Idle mode**, when the node is sensing the medium without performing any action.

The power levels associated to each mode are P_T, P_R and P_I, respectively, while the relationship between energy and power is given by $\mathcal{E} = P \cdot \ t$, where the terms $\mathcal{E}$, P and t represent the energy, the power and the time, respectively. Hence, taking into account the network topology, we have:

$$\mathbf{E}[\mathcal{E}_{succ}] = p_s \cdot (P_T + J \cdot P_R + (n-1)(J+1) \cdot P_I) \cdot T_{tr} \quad (33)$$

$$\mathbf{E}[\mathcal{E}_{idle}] = p_i \cdot (n + l) \cdot P_I \cdot \sigma \quad (34)$$

$$\mathbf{E}[\mathcal{E}_{col}] = p_c \cdot (\mathbf{E}[K] \cdot P_T + \mathbf{E}[K] \cdot J \cdot P_R + (n - \mathbf{E}[K])(J+1) \cdot P_I) \cdot T_c \quad (35)$$

where the definitions of most parameters can be found in Section IV-A, while the term $\mathbf{E}[K]$ denotes the average number of source nodes involved in a collision, expressed as:

$$\mathbf{E}[K] = \sum_{k=2}^{n} k \cdot p_k \quad (36)$$

with p_k corresponding to the probability that exactly k stations are involved in a collision, computed as:

$$p_k = \frac{\binom{n}{k} s^{*^k} (1 - s^*)^{n-k}}{p_c}. \quad (37)$$

Similarly to the completion time analysis, the probabilities of having successful (p_s), idle (p_i) or collided (p_c) slots in the second phase of the dissemination differ in the two proposed game theoretic schemes. Hence, we use the values of the probabilities that we derived in Sections IV-A1 and IV-A2 in order to estimate the energy consumption in the distributed and the coordinated medium access scheme, respectively.

V. Performance Evaluation

We have developed a time-driven C++ simulator that executes the rules of the proposed game theoretic access schemes. Monte Carlo simulations have been carried out to validate our analysis and further evaluate the performance of the protocols. In this section, we present the simulation setup along with the experimental results.

A. Simulation Scenarios

Our experiments are focused on the second phase of the data dissemination, where the proposed game theoretic medium access techniques are applied to resolve the conflicts among the source nodes. We consider two different network topologies in order to assess the scalability and the flexibility of our schemes under different scenarios:

1) **Topology A:** There are n source nodes, each of them affecting 2 sink nodes ($J = 2$) in a network formulation similar to that illustrated in Fig. 1.
2) **Topology B:** There are n source nodes, each of them affecting all l sink nodes in the network ($J = l$).

Apparently, in both topologies, the source nodes have the same (highest) impact on the network during the data dissemination. In addition, as we have already mentioned, the nodes are capable of applying network coding to the packets to be transmitted, before further forwarding them. The goal of our scenarios is the dissemination of a bunch of data packets that constitute an RGB image of dimensions 256×256 (translated as 256 packets of 256 pixels). The resolution of the image and, consequently, the color "depth" of the pixels determine the packet length. In particular, a 4-bit "depth" (16-colors) results in 128 bytes, while an RGBA image (32-bit "depth") results in 1024 bytes packet payload. In our simulations we consider packet lengths of $PHY + MAC + NC_H + Payload$ bytes, where PHY and MAC are the physical and the MAC headers, respectively, with $PHY = 192$ bits and $MAC = 224$ bits. NC_H is the network coding header, while $Payload$ is the packet payload which varies between 128 and 1024 bytes with regard to the image resolution. The coding of the packets is performed over a finite Galois Field - GF(2^8), since it has been proven to be sufficient for linear independence among the packets [30]. The specific field implies that the number of the encoding packets reflects to the number of the bytes in the encoding vector. If we use one generation of 256 packets, the extra overhead in each packet will be 256 bytes, which is huge especially for small size payloads. Therefore, we have chosen to create 16 generations of 16 packets each, which results in NC_H of 17 bytes in total (16 bytes for the encoding vector, 4 bits for the generation size and 4 bits for the generation identifier).

The time slot in our system has been selected equal to 20μsec according to the IEEE 802.11g physical layer [26], while the power level values have been chosen according to wireless interface power consumption measurements [27]: $P_T = 1900mW^5$, $P_R = P_I = 1340mW$.

In order to evaluate our game theoretic approaches, we compare the proposed policies with the Distributed Coordination Function (DCF) of the legacy IEEE 802.11g [26] where backoff windows are used to reduce the collisions among the source nodes. We consider the multicast operation of IEEE 802.11g, since there is no need for transmitting explicit ACK packets, while we adopt a minimum contention window (CW_{min}) equal to 32. The simulation parameters are summarized in Table III.

TABLE III
SYSTEM PARAMETERS

Parameter	Value	Parameter	Value
Packet Payload	128-1024 bytes	σ	20 μs
MAC+PHY Header	52 bytes	*NC Header*	17 bytes
Data Tx.Rate	54 Mb/s	*Generation Size*	16
CW_{min}	32	*DIFS*	50μs
P_T	1900 mW	P_I, P_R	1340 mW

B. Performance Results

The application of our strategies in different scenarios aims at their comprehensive evaluation, studying different aspects of the proposed techniques such as scalability (Topology A) and flexibility (Topology B). We therefore present the performance results separately for the two topologies. However, before proceeding to the protocols assessment, we try to justify our choice to use a GF(2^8) for packet coding.

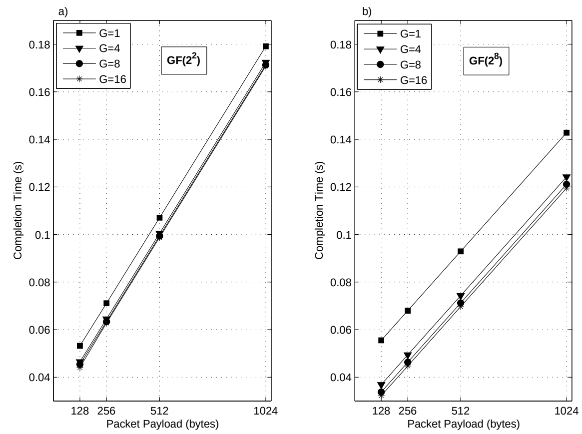

Fig. 5. Network coding impact on the dissemination completion time for a) GF(2^2) and b) GF(2^8) ($b = 1.0, n = 3$, Topology A)

Figure 5 highlights the impact of network coding on the system performance under the distributed access strategy. In particular, Fig. 5a and Fig. 5b present the completion time for different number of coding generations (G), selecting the coefficients from a finite GF equal to 2^2 or 2^8, respectively. In both cases, it can be clearly observed that the creation of various generations has a positive influence in the system performance. It is also worth noting the tradeoff between the packet overhead and the decoding probability with respect to the selected GF. Although higher GF implies higher overhead, the linear independence (decoding) probability is significantly higher. Hence, the number of required transmissions is reduced, thus providing a better system performance.

a) Topology A: Figure 6 presents the data dissemination completion time under the proposed game theoretic policies in Topology A for different number of source nodes ($n = 3, 7, 15$), assuming $b = 1.0$. First, we can see that the numerical results almost perfectly coincide with the analytical ones, thus verifying our theoretical derivations. In this figure, we can see that the coordinated approach outperforms the distributed access policy, with the gain, though, coming at the expense of having a central controller in the network. It is also worth noticing that the relative gain grows as the number of source nodes in the network increases.

In Fig. 7, we can see the completion time of the dissemination in our proposed game theoretic schemes, compared to a pure centralized solution where the central controller schedules the total transmissions by polling the stations in the network. Let us recall that our main motivation for the introduction of the game theoretic coordinated scheme was the excessive overhead that is caused due to the polling control packets. Interesting tradeoffs and useful conclusions can be derived by Fig. 7, where we study the performance of the protocols for various packet payloads, assuming $n = 2$ and $n = 12$ source nodes in the network. A straight-forward observation is that the

[5]The value of P_T has been selected as an average value of transmission consumed power, since it varies according to the Radio Frequency (RF) power level.

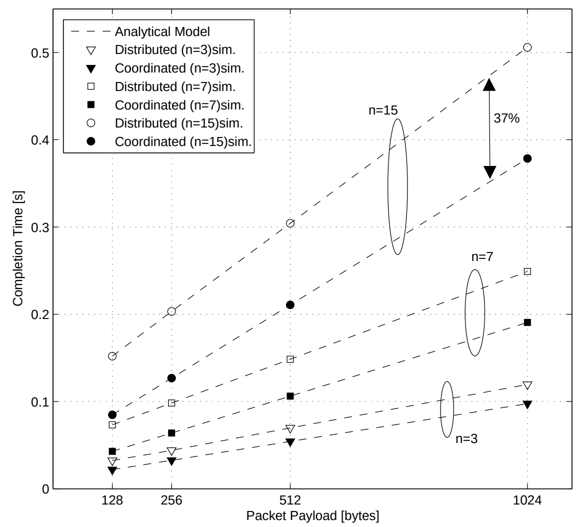

Fig. 6. Data dissemination completion time in Topology A (Distributed vs. Coordinated MAC strategy)

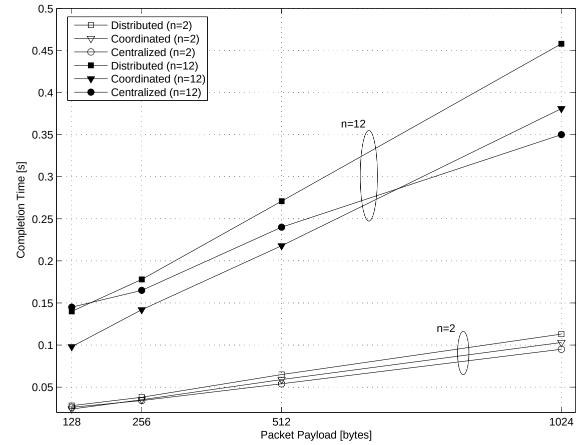

Fig. 7. Game Theoretic Strategies vs. Centralized Polling Access

overhead effect is extremely high in small packet payloads, as the size of the control packets is comparable to the data packets size. In case of $n = 2$, the centralized approach slightly outperforms the game theoretic access strategies, achieving a negligible reduction to the dissemination completion time. On the other hand, in case of $n = 12$ and small packet payload ($Payload = 64$ bytes), the control overhead significantly affects the data dissemination and, as a result, our both strategies outperform the pure centralized solution. As the packet payload increases, the coordinated game theoretic strategy continues to achieve lower completion time than the centralized protocol which, in turn, outperforms the distributed approach, since the control overhead is compensated by the impact of collisions[6]. It is also worth mentioning that the offloading of the central controller can bring several collateral advantages, particularly in scenarios with many nodes in the network that do not participate in the data dissemination. In such scenarios, the individual polling of every node would deteriorate further the completion time, since not every transmission would be beneficial for the data dissemination.

Figure 8 plots the analytical and the numerical results with regard to the energy efficiency performance of game theoretic strategies compared to the IEEE 802.11 Standard, considering five and fifteen sources ($n = 5$ and $n = 15$, respectively) in networks of Topology A. In this figure, we can see that our analytical model is validated, since the deviation from the simulation results is almost negligible. In addition, we observe that the proposed game theoretic policies are proven to be more energy efficient than the legacy DCF, with gains ranging from 48% up to 260% for particular scenarios (i.e., coordinated approach, $n = 5$, $Payload = 128$ bytes). It is also worth noticing that the distributed game theoretic strategy outperforms the IEEE 802.11 Standard in all cases, independently of the packet payload and the number of active source nodes in the network.

[6]According to the Internet Engineering Task Force (IETF) [31], the preferred transmission unit size for IP/non-IP based wireless communication systems is 254 bytes or less.

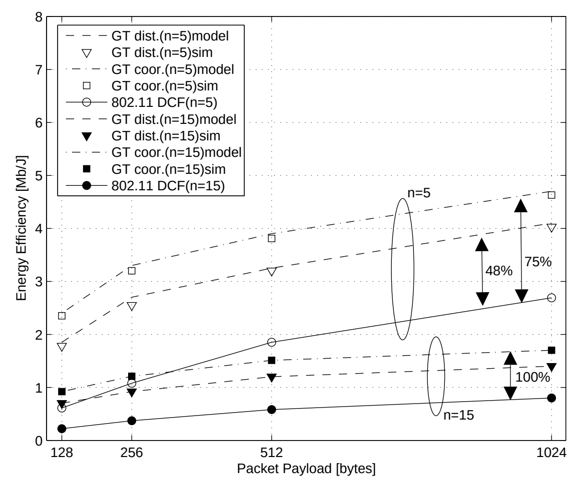

Fig. 8. Energy efficiency of game theoretic MAC strategies vs. IEEE 802.11 DCF ($b = 1.0$, Topology A)

b) Topology B: Figure 9 plots the dissemination completion time considering seven source nodes ($n = 7$) in a network of Topology B. In this case, the completion time is significantly lower compared to the scenarios of Topology A, since all nodes in the network are in one-hop distance and, hence, the dissemination time does not depend on the number of sink nodes. Comparing our two approaches, it is evident that the coordinated approach achieves a better performance, especially for the transmission of small data packets. As the packet payload increases, the relative gain between the two strategies decreases, remaining in all cases over 30%.

Figure 10 illustrates the simulation results with regard to the dissemination completion time of our proposed game theoretic access schemes versus the legacy IEEE 802.11 DCF in Topology B networks. In this particular experiment, the

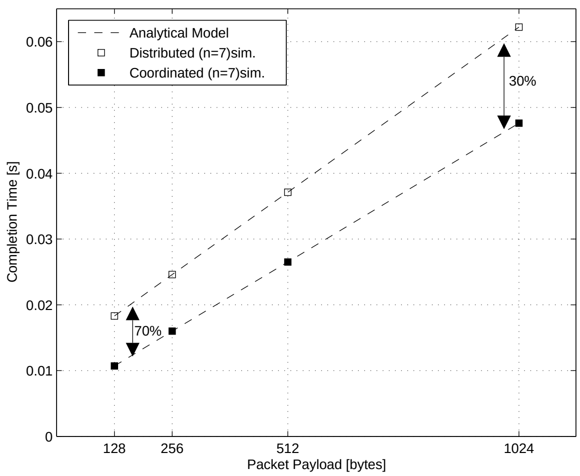

Fig. 9. Data dissemination completion time in Topology B (Distributed vs. Coordinated MAC strategy)

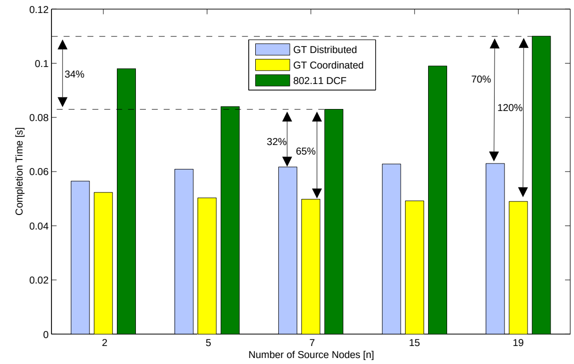

Fig. 10. Data dissemination completion time vs. Number of source nodes ($b = 0.8$, $P = 1024$ bytes)

number of source nodes varies between 2 and 19, assuming $b = 0.8$ and $Payload = 1024$ bytes. In this figure, we observe the great time enhancement that the game theoretic approaches offer comparing to the IEEE 802.11 Standard. In particular, the distributed access strategy improves the completion time up to 80% ($n = 2$), while the improvement under the coordinated approach exceeds 100%. With respect to the lowest dissemination completion time for the DCF ($n = 7$), the distributed and the coordinated approach achieve gains of 32% and 65%, respectively. The second worthwhile observation concerns the dependence between the dissemination completion time and the number of source nodes in the network. More specifically, the flexibility of game theoretic access strategies allows for their smoothest adaption in networks with many sources. Therefore, the dissemination completion time in our proposed schemes is not significantly affected by the total number of source nodes. On the other hand, we can see that the contention window dynamics in IEEE 802.11 are not able to bound the dissemination completion time, a fact that can be intuitively conceived by considering the backoff mechanism operation. More specifically, in case of few (e.g., $n = 2$) or many (e.g., $n = 19$) source nodes in the network, the completion time increases by either idle slots or collisions, respectively, generating a fluctuation of approximately 34%.

Figure 11 presents the energy efficiency performance of the proposed strategies in networks of Topology B, assuming $n = 3$ and $n = 19$ sources in the network in order to study the scalability of our policies. With regard to the case where $n = 19$, we can see that the gain we achieve applying the distributed game theoretic access strategy remains steadily over 100% compared to the DCF, while the coordinated policy increases this yield up to 300%. On the other hand, we observe a slightly different trend in the case of few source nodes in the network ($n = 3$). In this case, the gain of the distributed access strategy over the IEEE 802.11 Standard decreases as the packet payload grows, even though the initial gain for payload of 128 bytes reaches 100%. This fact can be explained by considering again the DCF implementation, which is designed to avoid collisions. This design is beneficial for packets of high payload but, on the contrary, creates idle slots in the network, thus affecting the energy performance for small packet payloads. Our proposed adaptive game theoretic strategies handle these points efficiently, hence dealing effectively with energy efficiency issues.

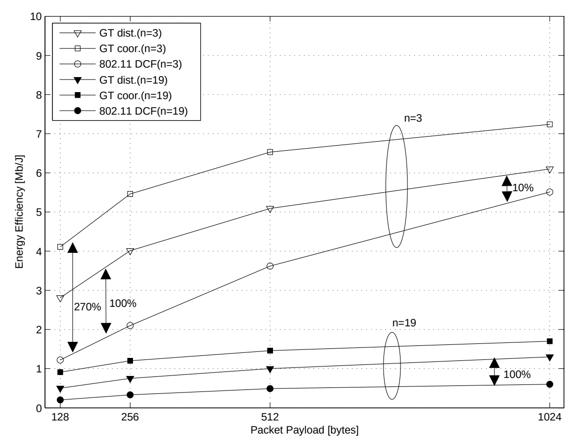

Fig. 11. Energy efficiency of game theoretic access strategies vs. IEEE 802.11 DCF ($b = 1.0$, Topology B, $l = 1$)

VI. Concluding Remarks

In this paper we studied MAC issues for data dissemination scenarios. We introduced two novel game theoretic strategies to resolve the conflicts caused by the existence of multiple active source nodes in the network. The first approach is a distributed access strategy, where the nodes estimate their steady state transmission probabilities (*NE*) such that to maximize their lifetime, using energy-based utility functions. In the second, coordinated approach, we consider the existence of a central controller that is occasionally used to resolve the conflicts, thus bounding the dissemination completion time. In addition, in all cases the exchanging of ACK packets is eliminated by applying network coding techniques.

Compared to the legacy DCF of the dominant IEEE 802.11 Standard, our proposed protocols achieve significant enhancement in terms of energy consumption, since they were proven to be up to 3 times more energy efficient, without degrading the offered QoS. Regarding the time that is required to disseminate all packets in the network, we demonstrated (both analytically and experimentally) that our schemes clearly outperform IEEE 802.11, since the completion time is considerably reduced. Our results clearly showcase the need of designing new, adaptive MAC protocols for wireless networks, and highlight the game theory as an appropriate tool towards this direction. In our future work we plan to evaluate the proposed strategies in the presence of analog network coding in the system.

Acknowledgments

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