

Brief Announcement: Game Theoretical Approach for Energy-Delay Balancing in Distributed Duty-Cycled MAC Protocols of Wireless Networks

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ABSTRACT

Optimizing energy consumption and end-to-end (e2e) packet delay in energy constrained distributed wireless networks is a conflicting multi-objective optimization problem. This paper investigates this trade-off from a game-theoretic perspective, where the two optimization objectives are considered as virtual game players that attempt to optimize their utility values. The cost model of each player is mapped through a generalized optimization framework onto protocol specific MAC parameters. A cooperative game is then defined, in which the Nash Bargaining solution assures the balance between energy consumption and e2e packet delay. For illustration, this formulation is applied to three state-of-the-art wireless sensor network MAC protocols; X-MAC, DMAC, and LMAC as representatives of preamble sampling, slotted contention-based, and frame-based MAC categories, respectively. The paper shows the effectiveness of such framework in optimizing protocol parameters for achieving a fair energy-delay performance trade-off, under the application requirements in terms of initial energy budget and maximum e2e packet delay. The proposed framework is scalable with the increase in the number of nodes, as the players represent the optimization metrics instead of nodes.

Categories and Subject Descriptors

C.2.2 [Network Protocols]; C.2.4 [Distributed System]; G.1.6 [Mathematics of computing]: Optimization—*Convex programming*

Keywords

Wireless Networks; Game Theory; Duty-Cycling; MAC; Energy; Delay.

1. INTRODUCTION

Maximizing the network lifetime while assuring the application requirements in terms of e2e delay is challenging in distributed energy-constrained wireless networks, such as wireless sensor networks (WSN). Energy saving is achieved at the MAC protocol by duty-cycling the radio, which necessitates multiple operational cycles in forwarding data packets. This mecha-

nism can violate the e2e delay bound required in multi-hop networks. Given the application constraints in terms of initial energy budget devoted to each individual node and the maximum e2e packet delay tolerated, the choice of MAC protocol's parameters is of great importance; yet their choice is currently done by system designers based on repeated real experiences [2], or on optimizing one objective subject to other objectives as constraints [12]. These solutions achieve the optimal running performance for one objective that is not necessarily optimal for the other, which yields a performance far off the application requirements.

Contribution: We investigate the inherent trade-off between the two metrics from a game-theoretic perspective. We propose a game-theory framework that permits to determine optimal values for tunable MAC parameters to achieve a fair energy-delay trade-off for design considerations. These tunable parameters, related to application sampling and MAC duty-cycle operations, allow to find an equilibrium point in which the system operates. In the proposed framework, the virtual players are the performance metrics (energy and delay), instead of the individual nodes that is common in the state-of-the-art models. The cost model of each player is then mapped onto a protocol specific MAC parameters that are system wide optimal. The following steps are followed in order to find the optimal operation that balances energy consumption and latency: (i) Energy and Latency are characterized in duty-cycle MAC protocols according to sampling rate and duty-cycle operation parameters. (ii) Energy consumption optimization is achieved by deriving optimal parameters that minimize energy consumption subject to latency constraints. (iii) Latency optimization is achieved by deriving optimal parameters that minimize latency subject to energy budget constraints. Finally, (iv) a Nash Bargaining solution model is used to find a cooperative optimal point between players that represent energy consumption and latency.

Related Work: While most of the energy-efficient MAC protocols for wireless networks followed pure experimental approaches, some works have attempted to model and analyze these protocols. Langendoen and Meier, [3] consider traffic and network models for very low data rate applications, and they analyze energy consumption and average latency of well known MAC protocols. Protocol optimization have been investigated by Ye et al. [10], notably for energy minimization of SCP-MAC protocol. While most models consider single- objective optimization, protocol optimization under application needs in terms of both energy and e2e delay have been considered in [12]. However, their approaches are based on optimizing energy subject to constraints on the delay. Lately, numerous efforts have been devoted to address MAC optimization in wireless networks using game theory. First, Nuggehalli et al [7] use game-theory to address the QoS support in 802.11 networks that enables users with high-priority or low-priority traffic to fairly negotiate channel access. Energy-efficiency is also addressed by Voulikidis et al. [9], using game-theory-based coalition formation between spatial correlated sensors to reduce the amount of transmitted packets. The energy-delay tradeoff is considered by Nahir et al, [5], where multiple cost models (power level, direct/indirect transmissions) are used by each node to determine the Nash equilibrium point. All these works consider nodes as players

in the game and attempt to maximize the defined utility function. These approaches lack of scalability and do not apply to large networks. Last but not the least, Zhao et al. [11] propose a game-theoretical solution to achieve a trade-off between load-balancing and energy-efficiency in traffic engineering, where the performance goals are considered as peers (players) of the game. The proposed framework is based on the energy model derived in [3], and it uses of the Nash Bargaining solution to balance objectives modeled as virtual players, which is inspired by the model proposed in [11]. To the best of our knowledge, this work is the first that considers the energy/delay trade-off in duty-cycled MAC protocols using game-theory.

2. GAME THEORY FRAMEWORK

In the proposed framework, the key performance metrics are the energy consumption E and the maximum end-to-end (e2e) packet delay L . The application requirements expressed as the maximum energy budget per node, E_{budget} , and the maximum allowed end-to-end delay per node, L_{max} , are used as inputs for the framework. The framework builds then a system-wide model for energy and delay based on, (i) the specified MAC model defined by its operating modes: idle, transmission, reception, and sleep modes, and (ii), the network and traffic models that permit to determine the topology information and the traffic load at each node.

Energy Consumption, E^n , is defined as the amount of energy consumed by the radio of node, $n \in V$ (V a set of nodes in the network), according to its position and the amount of traffic it handles. Thus, the Energy Consumption depends on node density and data sampling rate. It is calculated as a function of the operating modes the sensor node runs, and the MAC intrinsic parameters. In general, the energy consumed in any MAC protocol is due to: carrier sensing E_{cs} , data transmission E_{tx} , data reception E_{rx} , overhearing E_{ovr} , and sending/receiving synchronization frames (resp. E_{stx} and E_{srx}) in the case of synchronous protocols. Given that the network lifetime can be expressed as the expected shortest node-lifetime [12], we define the system wide Energy Consumption, E , as the maximum consumed energy in the network,

$$E = \max_{n \in V} (E^n = E_{cs}^n + E_{tx}^n + E_{rx}^n + E_{ovr}^n + E_{stx}^n + E_{srx}^n)$$

End-to-end (e2e) Delay, L^n , is defined as the expected time between the first transmission of a packet at node, $n \in V$, and its reception at the sink. It is then a per-topology parameter, in the sense that it depends on the position of the node that generates the data. L^n denotes the sum of per-hop latencies of the shortest path \mathcal{P}^n from node n to the sink, where L_l^n is the one-hop latency on link $l \in \mathcal{P}^n$. The maximum end-to-end latency, L , is defined as the maximum latency from all nodes to the sink as follows:

$$L = \max_{n \in V} (L^n = \sum_{l \in \mathcal{P}^n} L_l^n)$$

Network and Traffic Model. Let us consider an unsaturated network with low traffic, which is typical in energy-constrained networks, e.g., WSN applications. For the sake of simplicity, a ring topology is adopted following the same analysis as in [3]. A spanning tree is constructed, where nodes are static and maintain a unique path to the sink and use the shortest path routing with a maximum length of D hops; the depth or number of rings of the tree. Assume a network with uniform node density on the plane, and a unit disk graph communication model with density, C , i.e., unit disks contain $C+1$ nodes. The nodes are layered into levels according to their distance to the static sink in terms of minimal hop count, d ($d=1, \dots, D$), where $d=0$ is reserved for the sink. Periodic traffic generation is considered, where every source node generates traffic with frequency F_s . Consequently, the same input F_I^d , output F_{out}^d , background F_B^d traffic and input links I^d equations for every node are similar to those derived in [3].

Energy-Delay Optimization. Let Θ denote the set of parameters that can be optimized in the system for a given application. Given a specific MAC protocol, let $X \in \Theta$ be the vector of system parameters that can be optimized. The following optimization problems are defined for energy consumption and e2e delay minimization:

<p>(P1)</p> <p>Minimize $E(X)$</p> <p>S.t. $L(X) \leq L_{max}$</p> <p>Var. X,</p>	<p>(P2)</p> <p>Minimize $L(X)$</p> <p>S.t. $E(X) \leq E_{budget}$</p> <p>Var. X,</p>
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The pairs (E_{best}, L_{worst}) and (E_{worst}, L_{best}) are the optimal solutions of problems (P1) and (P2) respectively, where, $E_{best}=E(X_E^*)$

and $L_{worst}=L(X_E^*)$, while $E_{worst}=E(X_L^*)$ and $L_{best}=L(X_L^*)$.

Nash Bargaining Solution. In order to find the optimal trade-off, we use the Nash Bargaining solution where every optimization problem represents a player, i.e., player *Energy* and player *Latency*. A bargaining game with two players selects one of the possible player's outcomes of a joint collaboration [6]. Let $A \in R^2$ be the set of alternatives the players face, $S=\{s = (u_1(a), u_2(a)) | a \in A\}$ be the set of feasible utility payoffs u , and $v \in S$ be a disagreement or *threat* point. Each point in S corresponds to the outcome of the bargaining and specifies the utility for this outcome. The disagreement point, $v = (v_1, v_2)$, represents the value that each player expects to receive if the negotiation breaks down. The goal of the bargaining is to choose a feasible agreement $\Phi : (S, v) \rightarrow S$ that results from the negotiation. The Nash Bargaining solution considers that S is convex, compact, and there exists an $s \in S$ such that, $s > v$ for both players. Players have complete information over S, v . The Nash Bargaining solution deals with the bargaining game by solving optimization problem (NBS):

<p>(NBS)</p> <p>Maximize $(s_1 - v_1)(s_2 - v_2)$</p> <p>S.t. $s \in S$</p> <p>Var. $s, (s_1, s_2) \geq (v_1, v_2)$</p>	<p>(P3)</p> <p>Maximize $(E_{worst}-E)(L_{worst}-L)$</p> <p>S.t. $(E_{budget}, L_{max}) \geq (E, L)$</p> <p>Var. $E, L, (E_{worst}, L_{worst}) \geq (E, L)$</p>
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The Nash Bargaining solution has the following axioms, [6], (i) *Pareto Optimality*, (ii) *Symmetry*, (iii) *Scale Independence*, and (iv) *Independence of Irrelevant Alternatives*. It specifies that there exists an optimal solution since S is compact, the objective function is continuous. The uniqueness of the optimal solution is guaranteed when the objective function is quasi-concave. The Nash Bargaining solution $\Phi(S, v)$ is the unique bargaining solution that satisfies the previous four axioms. Let X_E^* and X_L^* be the point values obtained by both players, Energy and Delay, if the agreement for problems (P1) and (P2) fails. Noting that E and L are cost functions instead of utility functions, and that the pair (E_{best}, L_{best}) is an infeasible solution in both problems (P1) and (P2). The Nash Bargaining Solution to the Duty-Cycled MAC problem is given by problem (P3). Each player can prevent the agreement threatening with his best value and the other's worst value, or it can reduce its threat, looking for a feasible point that satisfies both players. The solution (E^*, L^*) of the optimization problem (P3) will be the optimal cost for both players under the agreement.

3. APPLICATION TO DUTY-CYCLED MAC PROTOCOLS

We apply the optimization framework to three state-of-the-art energy-delay efficient MAC protocols, X-MAC [1], DMAC [4], and LMAC [8] as representatives of the main categories of duty-cycled MAC protocols, asynchronous preamble sampling, slotted contention-based, and frame-based respectively. The application to these protocols exemplify the framework and show its usefulness to optimize different MAC parameters that permit to achieve a fair energy-delay trade-off. The per-node energy consumption based on the protocol operation modes, the e2e packet delay, and the bottleneck constraint are provided in [3].

Energy Optimization: Given the application requirements in terms of e2e packet delay bound L_{max} , energy optimization derives optimal MAC parameters that give the minimal network energy consumption subject to maximum e2e packet delay. Let X_i^* be the optimal point of problem (P1) with $i=\{XMAC, DMAC, LMAC\}$. Then, the optimal values of problem (P1) are $E_{best}^i = E^i(X_i^*)$. The corresponding e2e packet delays are obviously non-optimal, $L_{worst}^i = L^i(X_i^*)$.

Delay Optimization: Given the application constraints in terms of initial energy budget E_{budget} , the delay optimization problems can be solved similarly to the energy optimization models, except the fact that the largest delay occurs at the outer ring nodes, $d=D$. Let Y_i^* denotes the optimal point of problem (P2) with $i=\{XMAC, DMAC, LMAC\}$. The optimal delay values of problem (P2) are denoted $L_{best}^i = L^i(Y_i^*)$. The network energy consumption is non-optimal for this point, and it is denoted by: $E_{worst}^i = E^i(Y_i^*)$.

Energy-Delay Tradeoff: The Nash Bargaining solution (P3) is applied in the following to the three protocols. Let the point $(E_{worst}^i, L_{worst}^i)$ be the disagreement point¹ with $i=\{XMAC, DMAC, LMAC\}$. Both

¹Note that although the energy is considered at nodes at ring $d=1$, and latency at nodes $d=D$, the game is not played by the nodes, but it is played later at the system level.

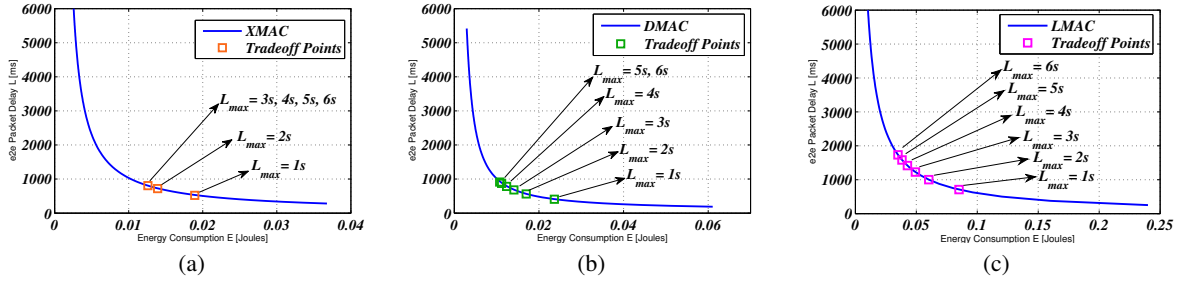


Figure 1: E-L trade-off when fixing $E_{budget}=0.06$ J for (a) X-MAC, (b) DMAC, and (c) LMAC.

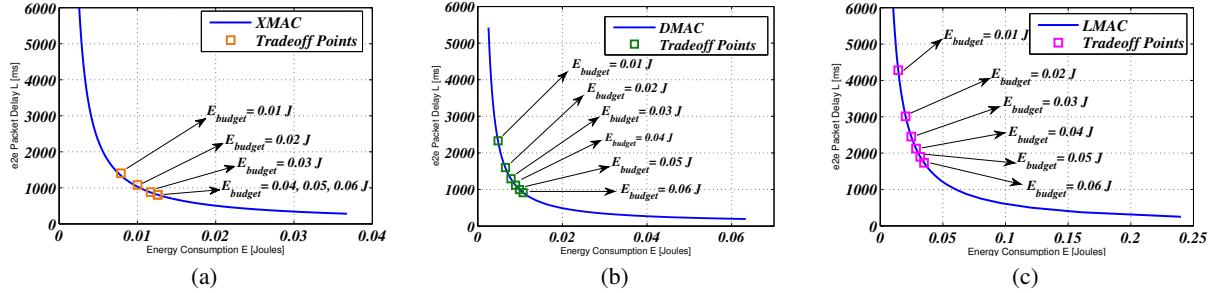


Figure 2: E-L trade-off when fixing $L_{max}=6$ s for (a) X-MAC, (b) DMAC, and (c) LMAC.

players can threat with their optimal values E_{best}^i and L_{best}^i . The problem (P3) is non-linear non-convex. The authors of [11] show how to transform similar problems into a standard convex optimization problem without changing its solution. The idea is to define auxiliary variables E_1 and L_1 such that $E_1=E^i(X)$ and $L_1=L^i(X)$, which should be satisfied by the optimal solution. Whenever the problem (P3) is feasible, $E^i(X) \leq E_{worst}^i$, $L^i(X) \leq L_{worst}^i$, and application of (P3) to the MAC protocols yields a concave problem (P4) with $i=\{XMAC, DMAC, LMAC\}$.

$$\begin{aligned}
 \text{(P4)} \quad & \text{Maximize} \quad \log(E_{worst}^i - E_1) + \log(L_{worst}^i - L_1), \\
 & \text{s.t.} \quad (E_{worst}^i, L_{worst}^i) \geq (E^i(X), L^i(X)) \\
 & \quad \quad (E_1, L_1) \geq (E^i(X), L^i(X)) \\
 & \text{s.t.} \quad (E_1, L_1) \leq (E_{budget}, L_{max}) \\
 & \text{Var.} \quad E_1, L_1, X
 \end{aligned}$$

Optimal values of the parameters that ensure the Nash bargaining are obtained by resolving (P4) for every protocol (each with its specific formulas of energy and latency that yields the parameters). Results are analyzed in the following. Fig. 1.a (XMAC), Fig. 1.b (DMAC), and Fig. 1.c (LMAC) plots the results obtained by fixing E_{budget} to 0.06J, and L_{max} has been varied in [1sec, 6sec]. Fig. 2.a (XMAC), Fig. 2.b (DMAC) and Fig. 2.c (LMAC) plots the results obtained by when fixing L_{max} to 6sec and varying the E_{budget} in [0.01J, 0.06J]. As it can be observed from Fig. 1, relaxing the e2e packet delay bound (L_{max}) for every protocol leads to an agreement in favor to the energy consumption player, while rising the energy initial budget, E_{budget} , leads to an agreement in favor to the e2e packet delay player (as depicted in Fig. 2). As it is proved in [11], choosing the pair (E_{worst}, L_{worst}) in the Nash Bargaining Solution, leads to a solution that is proportional fair, i.e., that fulfills the following condition:

$$\frac{E^* - E_{worst}}{E_{best} - E_{worst}} = \frac{L^* - L_{worst}}{L_{best} - L_{worst}}$$

where (E^*, L^*) is the optimal point obtained by solving problem (P3).

Acknowledgments

This works is partly supported by Algerian Ministry of Higher Education through the DGRSDT, and the national Spanish funding TIN2010-21378-C02-01.

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