Efficient Routing for Correlated Data in Wireless Sensor Networks

Engin Zeydan
ezeydan@stevens.edu
Dept. Elect. and Comp. Engineering
Stevens Institute of Technology,
Hoboken NJ 07030

Didem Kivanc
didemk@ieee.org
Wireless Network Security Center,
Stevens Institute of Technology,
Hoboken NJ 07030

Cristina Comaniciu
ccomanic@stevens.edu
Dept. Elect. and Comp. Engineering
Stevens Institute of Technology,
Hoboken NJ 07030

***Abstract*— In this paper, we propose an efficient routing solution for correlated data collection in wireless sensor networks. Our proposed routing metric considers both the interference distribution as well as the data correlation when establishing routes. An iterative, distributed solution based on local information is proposed using a game theoretic framework. Routes are chosen to minimize both the interference impact of nodes in their neighborhood and the joint entropy of multiple sources relayed through common nodes.**

***Index Terms*— data aggregation, game theory, interference-aware routing, sensor networks**

I. Introduction

Energy efficient routing algorithms are of utmost importance for connectivity of wireless sensor networks (WSNs) [1] [2]. Many routing protocols have been proposed for WSNs emphasizing various metrics depending on the application and design specifications. Minimum energy routing (MER) in multi-hop wireless networks that accounts for the transmission power but not the interference between links is studied in [3] [4] [5]. Interference-aware routing strategies which are shown to give lower overall network energy consumption and higher throughputs than simple MER are given in [6] [7] for ad hoc networks. However, interference aware routing has not been explicitly studied in the context of WSNs.

In WSNs, the observed data from different nodes in a region is correlated and transmitting all this information can increase the traffic and data redundancy at the destination nodes. This may result in an inefficient energy consumption and inferior throughput of the overall network. Hence, only interference-aware routing without accounting for data correlations can give suboptimal results. Correlation-aware routing strategies without interference awareness are given in [8] [9]. In [8], the effect of spatial correlation on different routing schemes is studied. An empirical data correlation model is used for data aggregation at each node using experimentally obtained data. In [9], constructing an optimal network correlated data gathering tree for a general optimization problem is shown to be NP-complete. The authors thus resort to simulated annealing algorithms, which are known to be able to find close to optimal solutions for combinatorial problems, but are very computational expensive, and they are usually suitable as an off-line optimization method.

In this paper, we propose an energy efficient routing strategy for correlated data gathering problem. An interference and correlation aware routing is proposed such that the data aggregation and interference avoidance are performed simultaneously at each intermediate node. We exploit the potential of collaboration among sensors in data gathering and processing. We develop a simple game-theoretic model with different utility functions that account jointly or separately for interference and data correlation and compare the performances of these different routing strategies with numerical results. The quality of different routing paths is measured, and the potential advantage of our proposed approach is demonstrated.

The rest of the paper is organized as follows: In Section II, we define the system model. An efficient routing framework for effective throughput maximization is given in Section III. In Section IV, we present different facility cost selection choices for the congestion game and also show the convergence of our proposed algorithm. In Section V, we compare our proposed algorithms by numerical simulations. Finally, we provide the conclusions in Section VI.

II. System Model

We consider the problem of maximum data gathering through minimum interference created route with a single sink, to which all the data has to be sent. Let the network graph $G=(V,E)$ consist of all nodes V, where $|V|=N+1$, with E consisting of edges between nodes that can communicate with each other. We assume that there are $N/2$ sources, labeled Y_1 through $Y_{N/2}$, $N/2$ relay nodes and a sink, labeled D. We consider synchronous direct-sequence CDMA (DS-CDMA) where all nodes use a variable spreading sequences of length L. The spreading factor, L, can be adjusted depending on the channel quality and quality-of-service (QoS) requirements.

The energy per bit $E_b^{i,j}$ for a packet transmissions between nodes i and j can be defined similarly as in [7]:

$$E_b^{i,j}=\frac{MP_i}{mR_{i,j}P_c(\gamma)}, \tag{1}$$

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where M is the packet length, m is the information bits in a packet, P_i is the constant transmit power for all i, $R_{i,j}$ is the transmission rate or throughput between nodes i and j where $R_{i,j} = W/L_{i,j}$ and W is the system bandwidth, $L_{i,j}$ is the minimum spreading gain that can be employed between nodes i and j to reach a target signal to interference ratio (SIR) γ^*, $P_c(\gamma)$ is the probability of a correct reception, which depends on the achieved SIR, γ. If we assume no error correction capability, $P_c(\gamma) = (1 - BER)^M$. In this paper, we employ a non-coherent frequency shift keying modulation for which $BER = 0.5\exp(-0.5\gamma)$.

The minimum spreading gain between the nodes i and j is [7]

$$L_{i,j} = \frac{\gamma^* \sum_{k=1,k\neq i,j}^{N} h_{k,j} P_k}{h_{i,j} P_i - \gamma^* \sigma^2}, \quad (2)$$

where the link gain $h_{i,j} = 1/d_{i,j}^2$, $d_{i,j}$ is the distance of between the nodes i and j, σ^2 is the thermal noise.

It is assumed that data collected by the sensor nodes is correlated over geographical regions. Each source node Y_i generates a certain amount of information $H(Y_i)$, where $H(Y_i)$ is the entropy of source Y_i. As shown in Fig. 1, the nodes in the network can either send their own raw data directly into the sink, or if there are other nodes connecting to it, they can use the raw data from other nodes to aggregate and send aggregated data to the sink. In other words, we will use the explicit communication model where nodes use the relayed side information to compress or aggregate their data. In this explicit communication model, as data flows within the intermediate nodes to the sink node it can be aggregated along the way [9].

For data aggregation, we use the more general model of [8] where the approximate average joint entropy of two sources $H(Y_i, Y_j)$ is modeled as a function of inter-source correlation ρ as

$$H(Y_i, Y_j) = H(Y_i) + (1 - \rho)H(Y_j), \quad (3)$$

where $\rho = \exp(-d_{Y_i,Y_j}/c)$ and d_{Y_i,Y_j} is the distance between source Y_i and Y_j, and c is a constant that specifies the coverage of spatial correlation in the data.

We will obtain the joint entropy of $q-1$ sources using node i as a relay with the constructive iterative technique of [8]. The algorithm, which we call as maximum correlated data aggregation (MCDA), is summarized in Table I. In our model, data is generated at each source node with rate $H(Y_i)$ if no side information is available from other nodes. If node i has side information available coming from $q-1$ other sources, $Y_1, \ldots, Y_{q-1}$ which use node i as relay, then $H(Y_i|Y_1, \ldots.., Y_{q-1}) = H(Y_i, Y_1, \ldots.., Y_{q-1}) - H(Y_1, \ldots.., Y_{q-1})$ is computed as in Table I. Note that, this algorithm carries out more exact compression and requires more computation than [9] where the joint conditional entropy of multiple sources is simplified to be a constant r and does not the depend on the number of nodes on which conditioning is done.

Given the above correlation model, the effective energy per bit transmission, accounting for data redundancy through correlation can be redefined to be:

TABLE I
MCDA ALGORITHM

1. Initialize a set $T_1 = \{Y_1\}$ where Y_1 is any node. Denote $H(T_i)$ as the joint entropy of nodes on set T_i, hence $H(T_1) = H(Y_1)$. Let V denote the nodes in T_i. Let $V_R = V \setminus T_i$
2. For $i = 2, ..., q-1$
   (a) Update T_i and V_R by adding a source Y_i where $Y_i \in V_R$, and Y_i is the closest node (in terms of Euclidian distance) to all the other nodes in T_{i-1}, i.e. $T_i \leftarrow T_{i-1} \bigcup Y_i$ and $V_R \leftarrow V_R \setminus T_i$
   (b) Let d_i be the shortest distance between Y_i and the set of nodes in T_{i-1}. Then calculate the joint entropy as $H(T_i) = H(T_{i-1}) + (1 - \exp(-d_i/c))H(Y_i)$
   Next i
3. Then joint entropy of $q-1$ sources is $H(Y_1, ..., Y_{q-1}) = H(T_{q-1})$

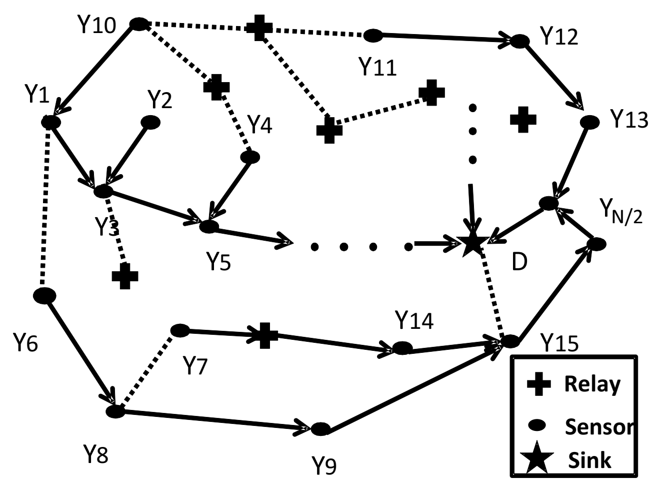

Fig. 1. Data from nodes Y_1,Y_2,...,$Y_{N/2}$ arrive at sink D by data aggregation through intermediate and relay nodes. Solid arrows show the chosen routes whereas dashed lines show the other possible routes.

$$\begin{aligned} E_{b,eff}^{i,j} &= E_b^{i,j} H_i(Y_1, Y_2, \ldots, Y_q), \\ &= \frac{MP_i}{m\, R_{i,j}\, P_c(\gamma)} H_i(Y_1, Y_2, \ldots, Y_q), \\ &= \frac{MP_i}{m\, \zeta_{i,j}\, P_c(\gamma)}, \end{aligned} \quad (4)$$

where $\{Y_1, Y_2, \ldots, Y_q\}$ denotes all the sources using node i and $H_i(Y_1, Y_2, \ldots, Y_q)$ is the joint entropy for all sources entering node i. We can see that, for this formulation, minimizing the effective energy per bit is equivalent to maximizing the effective throughput $\zeta_{i,j}$, given a required BER specification for the link. In what follows, we will look at the problem of maximizing the effective throughput of the network by efficiently selecting the routing paths.

III. Efficient routing framework for effective throughput maximization

Our joint optimization problem in the network and physical layers can be formulated as follows

$$\begin{aligned} \text{Maximize} \quad & \sum_{i=1}^{N/2} \sum_{k,l \in S_i} \zeta_{k,l} \\ \text{subject to} \quad & SIR_{k,l} \geq \gamma^*, \\ & P_k = C \ \text{ and } \ S_i \in X_i, \end{aligned} \tag{5}$$

where

$$\zeta_{k,l} = \frac{R_{k,l}}{H_k(\mathbf{Y}_k)}, \tag{6}$$

is the effective throughput between nodes k and l, C is the constant transmission power, $\mathbf{Y}_k$ is the set of all sources using node k, i.e. $\mathbf{Y}_k = \{Y_1, Y_2, \ldots, Y_q : k \in S_i\}$, S_i is the set of relaying nodes used for source Y_i, and X_i is the set of all possible relaying nodes for a route of source Y_i. Note that $\zeta_{k,l}$ changes when the source uses one of the relaying nodes, since the interference level on the overall network will change due to power transmission of each added relay node.

We redefine the effective throughput of each source Y_i as the minimum of the effective throughputs of all the links in a route, since the link with the least effective throughput determines the effective throughput of each source. This link is the bottleneck link for that particular source node. Hence, we rewrite the optimization problem as

$$\begin{aligned} \text{Maximize} \quad & \sum_{i=1}^{N/2} \zeta_i \\ \text{subject to} \quad & SIR_{k,l} \geq \gamma^*, \\ & P_k = C, \end{aligned} \tag{7}$$

where

$$\zeta_i = \min_{k,l \in S_i} \quad \zeta_{k,l} \ \text{ and } \ S_i \in X_i. \tag{8}$$

Note that finding the optimal effective throughput maximization algorithm is a hard optimization problem. We propose a game theoretic formulation which can be shown to converge to a local optimal solution with relatively low complexity and in a distributed fashion.

The above problem can be formulated as a congestion game model which can be shown to be isomorphic with a potential game. In this game, the players are the source nodes in quest for routes, the relaying nodes are the shared facilities, the action of the players is the selection of a group of facilities that form a route, and costs can be associated with various route selections.

Formally, the proposed game-theoretic routing model for correlation and interference aware routing considers the route selection of each sensor node as a congestion game Γ. The game Γ is a tuple $(\mathbf{N}, \mathbf{F}, (X_i)_{i \in \mathbf{N}}, (w_f)_{f \in \mathbf{F}})$ where $\mathbf{N} = \{Y_1, \ldots, Y_{N/2}\}$ denotes the set of players, i.e. the number of sources, $\mathbf{F} = \{1, \ldots, m_f\}$ is the set of facilities, X_i is the strategy space of player (or source) Y_i, and $w_f : \mathbf{N} \rightarrow \mathbb{Z}$ is a cost function associated with using the facility f. We define $\mathbf{S} = (S_1, \ldots, S_{N/2})$ as the state of the game in which player Y_i chooses strategy $S_i \in X_i$.

We define utility function for source Y_i in our congestion game as

$$u_i : \mathbf{S} \rightarrow \mathbb{R}, \ \ u_i(S_i, S_{-i}) = -\sum_{f \in S_i} w_f(S_i, S_{-i}), \tag{9}$$

where $S_{-i} = (S_1, S_2, \ldots, S_{i-1}, S_{i+1}, \ldots, S_n)$. The game performance is influenced by the selection of cost functions $w_f(S_i, S_{-i})$ for facilities. We propose and compare several metrics in the next section.

IV. Facility cost selection for the congestion game

We consider the problem of constructing the *maximum correlated data gathering with minimum interference tree*. In setting up the costs for facilities, we can consider several parameters:

1) Energy spent for relaying bits on outgoing links from the facility,
2) Interference impact of the facility of the neighborhood network,
3) Opportunity for aggregation.

A. Minimum Energy Routing (MER)

The classic approach is to consider only energy minimization. We denote this classic approach as MER (e.g. [4] [5]). For MER, the following utility function is used

$$u_i(S_i, S_{-i}) = -\sum_{f \in S_i} E_b^f, \tag{10}$$

where E_b^f is the cost of facility f, expressed in terms of energy per bit required on ongoing links from facility f, through the strategy (or route) S_i and S_{-i}.

B. Interference Aware Routing (IAR)

MER only accounts for formation of routes with minimum energy. However, energy efficiency and sensor lifetime may also be affected by the interference that a relay node might generate to its neighboring nodes. Therefore, interference impact awareness with MER must also be addressed in terms of route selection strategies. For this reason, IAR algorithms have been proposed in the context of ad hoc networks [6] [7]. For IAR, the following utility function is attempted to be maximized by each source Y_i

$$u_i(S_i, S_{-i}) = -\sum_{f \in S_i} \eta_f E_b^f, \tag{11}$$

where η_f is the nodes' normalized density. η_f is computed as the number of nodes surrounding each node depending on the circular region within a radius D_r. For a given cell radius D_r, η_f approximates the density of the nodes in a relay's vicinity and represents an estimate of the interference impact a node has on its neighbors [7]. Note that this approach results in simple implementation and requires only local information. It was shown in [6] [7] that IAR gives higher average throughput for overall network compared with MER for ad hoc networks. However, it is not clear if this is an optimum solution for WSNs, since sources generate correlated data.

C. CAR and ICAR

In WSNs, constructing the correlated data gathering routes is an important task for cost minimization [8] [9]. To account for data correlation and potential for data aggregation in the network, we propose correlation-aware routing (CAR) and interference and correlation aware routing (ICAR) game formulations. For CAR, given a network, the problem is to induce the formation of a maximal correlated data aggregation tree from each reporting sensors (sources) to the sink. For constructing the correlated data gathering routes of each source Y_i, we use the following utility function

$$\begin{aligned} u_i(S_i, S_{-i}) &= -\sum_{f \in S_i} E_b^f (H_f(\mathbf{Y}_f) - H_f(\mathbf{Y}_f^{-i})), \\ &= -\sum_{f \in S_i} E_b^f H_f(Y_i \mid \mathbf{Y}_f^{-i}), \end{aligned} \tag{12}$$

where $\mathbf{Y}_f = \{Y_1, Y_2, \ldots, Y_q : f \in S_i\}$ denotes all sources using the facility f, and all sources using facility f except source Y_i is denoted by $\mathbf{Y}_f^{-i} = \{Y_1, Y_2, \ldots, Y_q \setminus Y_i : f \in S_i\}$. In this approach, each user will try to maximize its own utility function to find the best routes that will result in maximum data aggregation.

An alternative approach, which considers both opportunities for aggregation and interference impact, is ICAR. ICAR consists of a combination of CAR and IAR. The solution provided by this algorithm consists of constructing the maximum correlated data gathering using the idea of CAR algorithm and minimum interference impact relaying nodes, as in the IAR algorithm. For ICAR, we define the cost of using a facility f

$$\begin{aligned} w_f(H_f(\mathbf{Y}_f)) &= E_b^f H_f(\mathbf{Y}_f)\eta_f, \\ &= E_{b,eff}^f \eta_f. \end{aligned} \tag{13}$$

We assume that the players act cooperatively and aim at choosing strategies $S_i \in X_i$ maximizing their utility functions, where the utility function $u_i(S_i, S_{-i})$ of source Y_i is given by

$$\begin{aligned} u_i(S_i, S_{-i}) &= -\sum_{f \in S_i} w_f(H_f(Y_i \mid \mathbf{Y}_f^{-i})), \\ &= -\sum_{f \in S_i} w_f(H_f(\mathbf{Y}_f) - H_f(\mathbf{Y}_f^{-i})). \end{aligned} \tag{14}$$

Note that the data aggregation at each facility node will be performed using MCDA algorithm for both ICAR and CAR after the routes are being established in simulations.

In summary, in Fig. 2, we illustrate a diagram of objectives of different routing schemes discussed above. Note that all algorithms, i.e. MER, IAR, CAR and ICAR are energy-aware, IAR is both energy and interference aware, CAR is both energy and correlation aware and ICAR is energy, interference and correlation aware.

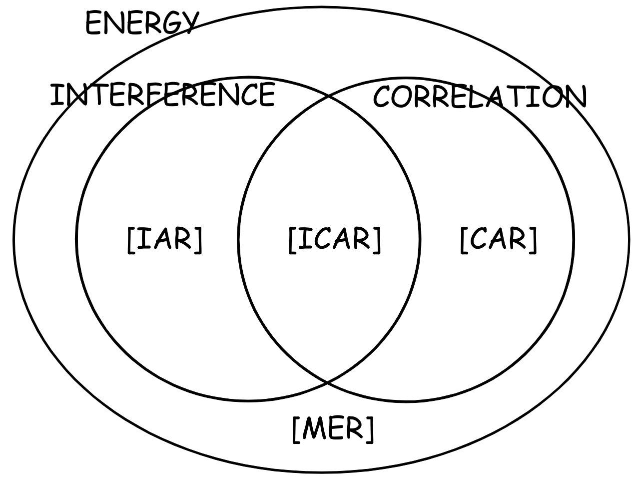

Fig. 2. Illustration of different energy efficient routing schemes with their objectives for WSNs.

D. A Potential Game Formulation for ICAR and CAR

In certain classes of games, the game converges to a Nash equilibrium when a best response adaptive strategy is employed. In what follows, we show that the congestion game associated with CAR and ICAR is isomorphic with a potential game, for which a best response strategy is shown to converge to a Nash equilibrium. More specifically, we can show that CAR and ICAR games are exact potential games, by defining a potential function for the game, that exactly reflects changes in individual utility functions.

A potential game is a normal form game such that any changes in the utility function of any player in the game due to an unilateral deviation by the player is reflected in a global function. A best response strategy is shown to converge to a Nash equilibrium if each player takes actions sequentially to maximize its utility [10]. Note that, while sequential updates may require additional synchronization overhead, a simple approximation implementation may be based on randomized access which on average will result in sequential updates. This can be shown experimentally to have minimal impact on convergence properties.

An exact potential function $\mathcal{P}(.)$ is defined as

$$\begin{aligned} \mathcal{P} : \mathbf{S} \rightarrow \mathbb{R}, \ \ \forall i \in \mathbf{N} \ \text{and} \ \ S_i, S_i' \in \mathbf{S}, \\ u_i(S_i, S_{-i}) - u_i(S_i', S_{-i}) = \mathcal{P}(S_i, S_{-i}) - \mathcal{P}(S_i', S_{-i}). \end{aligned} \tag{15}$$

We will demonstrate that interference and correlation aware routing with utility functions given by (14) is an exact potential game (EPG) with the potential function,

$$\mathcal{P}(S_i, S_{-i}) = -\sum_{f \in \mathbf{F}} w_f(H_f(\mathbf{Y}_f)). \tag{16}$$

Theorem : ICAR defined by utility function (14) and the potential function (16) is an EPG.

Proof: See the appendix. ■

Lemma : CAR with utility function defined by (12) is also an EPG with potential function,

$$\mathcal{P}(S_i, S_{-i}) = -\sum_{f \in \mathbf{F}} w_f(H_f(\mathbf{Y}_f)). \tag{17}$$

where $w_f(H_f(\mathbf{Y}_f)) = E_{b,eff}^f = E_b^f H_f(\mathbf{Y}_f)$.

Proof: The proof follows a similar approach as in theorem. ■

Hence, ICAR and CAR have been shown to converge to Nash equilibrium strategies by using a best response adaptive strategy.

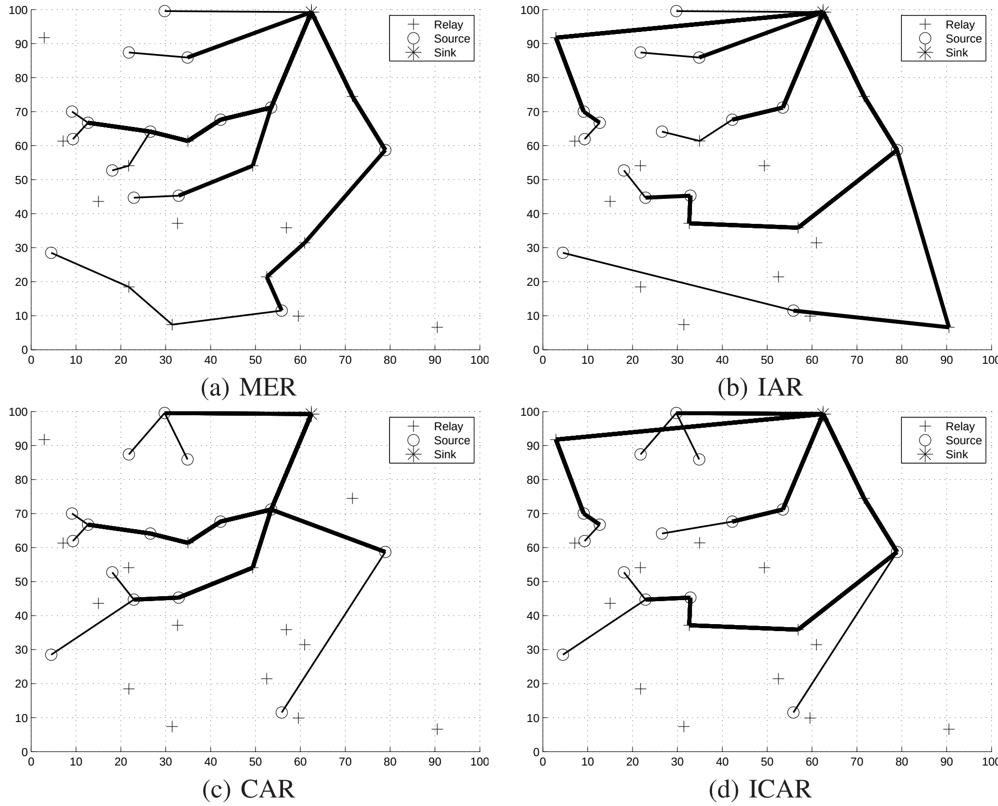

Fig. 3. Selected paths of each sources and the tree structures for each routing strategies in one of the considered scenario when $N = 30$. Thick lines indicate the data aggregation using MCDA algorithm.

V. Simulation Results

For numerical results, the number of nodes in the network is selected to be $N = 30$ uniformly distributed over a square area of dimension 100×100. The target SINR is selected to be $\gamma^* = 5$ dB and the noise power is $\sigma^2 = 10^{-13}$, which corresponds to thermal noise power for a bandwidth of $W = 1$ Mhz. We choose the equal transmit powers of all nodes C to be 70 dB above the noise floor. The spatial correlation of data is chosen to be $c = 100$.

The algorithm used for MER and IAR uses Dijkstra's algorithm to find the best routes from sources to sinks with one iteration. Although MER and IAR were not proposed in the context of data aggregation, we set-up the paths according to their corresponding utility functions, and then we aggregate data opportunistically based on the routes set-up using MCDA. CAR and ICAR are implemented iteratively based on the best response strategy described in the previous section.

In Fig. 3, we plot the branches of the constructed tree for different routing strategies, namely for MER, IAR, CAR and ICAR. Thick lines indicate the regions where the MCDA algorithm is called, i.e. the data aggregations are performed.

Our experiments show important average effective throughput improvements of ICAR algorithm over CAR, IAR and MER algorithms as shown in Fig. 4. We have simulated different routing algorithms with 100 different network configurations. Fig. 3 shows one of the considered scenario. In terms of average effective throughput, ICAR performs better than the other algorithms. Namely, for ICAR the average effective throughput improvements are of the order of 12% over CAR, 10% over IAR and 25% over MER. In these results, D_r is selected to be 17% of the dimension of one side of network deployment area (we found this value to maximize the performance of IAR). ICAR and CAR algorithms involve a small number of iterations after MER and IAR are established, and it can be implemented in a distributed fashion. Note also that, we start ICAR and CAR algorithms with the same tree structure as IAR and MER respectively, hence at first iteration their average effective throughput values are equal. From Fig. 4, we can also see that IAR performs 2% better than

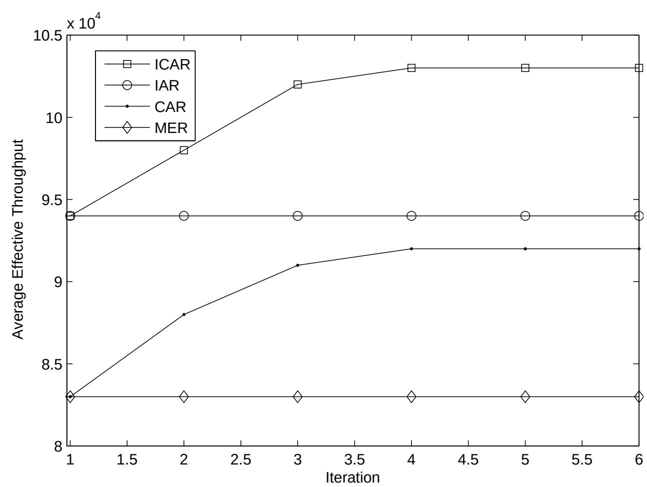

Fig. 4. Average effective throughputs of MER, IAR, CAR and ICAR throughout the iteration process when $N = 30$.

CAR at this moderate interference environment. However, it has been shown in [7], that the gains of IAR diminish for very low, or very high interference environments.

VI. Conclusion

In this paper, we addressed the problem of efficient transmission structure in wireless sensor networks where each source transmits correlated data over intermediate nodes to the sink. We have investigated the impact of interference, as well as efficient data aggregation in establishing routing paths towards the sink. We have proposed distributed iterative protocols based on a game theoretic framework, which are shown to converge within a couple of iterations. We have shown that, by accounting for both correlation structure and interference impact in constructing routes, significant effective throughput gains over classic approaches can be achieved.

Appendix

Proof of Theorem

Suppose there exists a potential function of the congestion game Γ:

$$\mathcal{P}(S_i, S_{-i}) = -\sum_{f\in\mathbf{F}} w_f(H_f(\mathbf{Y}_f)). \tag{18}$$

Let $S_i \in \mathbf{S}$ be the strategy of source $Y_i, i = 1, ..., N/2$, i.e. the collection of nodes used for relaying and $S_i' \in X_i$ be another strategy. Then,

$$\begin{aligned}\mathcal{P}(S_i, S_{-i}) &= -\sum_{f\in\mathbf{F}} w_f(H_f(\mathbf{Y}_f)),\\ &= \left(-\sum_{f\in S_i\setminus S^*} w_f(H_f(\mathbf{Y}_f))\right) + \\ &\left(-\sum_{f\in S_i'\setminus S^*} w_f(H_f(\mathbf{Y}_f^{-i})) - \sum_{f\in S^*} w_f(H_f(\mathbf{Y}_f))\right) + \\ &\left(-\sum_{f\in \mathbf{F}\setminus\{S_i \bigcup S_i'\}} w_f(H_f(\mathbf{Y}_f^{-i}))\right).\end{aligned} \tag{19}$$

where S^* denotes the common facilities used by the strategies S_i and S_i', i.e. $S^* = S_i \bigcap S_i'$. Define,

$$Q(S_{-i,-i'}) = -\sum_{f\in \mathbf{F}\setminus\{S_i \bigcup S_i'\}} w_f(H_f(\mathbf{Y}_f^{-i})). \tag{20}$$

Then,

$$\begin{aligned}\mathcal{P}(S_i, S_{-i}) &= \left(-\sum_{f\in S_i\setminus S^*} w_f(H_f(\mathbf{Y}_f))\right)\\ &+ \left(-\sum_{f\in S_i'\setminus S^*} w_f(H_f(\mathbf{Y}_f^{-i})) - \sum_{f\in S^*} w_f(H_f(\mathbf{Y}_f))\right)\\ &+ Q(S_{-i,-i'}).\end{aligned} \tag{21}$$

If source Y_i changes its strategy from S_i to S_i', then the potential function becomes,

$$\begin{aligned}\mathcal{P}(S_i', S_{-i}) &= \left(-\sum_{f\in S_i\setminus S^*} w_f(H_f(\mathbf{Y}_f^{-i}))\right)\\ &+ \left(-\sum_{f\in S_i'\setminus S^*} w_f(H_f(\mathbf{Y}_f)) - \sum_{f\in S^*} w_f(H_f(\mathbf{Y}_f))\right)\\ &+ Q(S_{-i,-i'}).\end{aligned} \tag{22}$$

Note that $Q(S_{-i,-i'})$ and $-\sum_{f\in S^*} w_f(H_f(\mathbf{Y}_f))$ are not affected by the strategy changing of source Y_i. Therefore,

$$\begin{aligned}\mathcal{P}(S_i', S_{-i}) - \mathcal{P}(S_i, S_{-i}) &= \left(-\sum_{f\in S_i\setminus S_i^*} w_f(H_f(\mathbf{Y}_f^{-i}))\right.\\ &\left.-\sum_{f\in S_i'\setminus S^*} w_f(H_f(\mathbf{Y}_f))\right) - \left(-\sum_{f\in S_i\setminus S^*} w_f(H_f(\mathbf{Y}_f))\right.\\ &\left.-\sum_{f\in S_i'\setminus S^*} w_f(H_f(\mathbf{Y}_f^{-i}))\right).\end{aligned} \tag{23}$$

From (14) and the definition for $w_f(.)$ in (13),

$$\begin{aligned}&u_i(S_i', S_{-i}) - u_i(S_i, S_{-i})\\ &= \left(-\sum_{f\in S_i'} w_f(H_f(\mathbf{Y}_f) - H_f(\mathbf{Y}_f^{-i}))\right) - \\ &\left(-\sum_{f\in S_i} w_f(H_f(\mathbf{Y}_f) - H_f(\mathbf{Y}_f^{-i}))\right),\\ &= \left(-\sum_{f\in S_i'\setminus S^*} w_f(H_f(\mathbf{Y}_f) - H_f(\mathbf{Y}_f^{-i}))\right) - \\ &\left(-\sum_{f\in S_i\setminus S^*} w_f(H_f(\mathbf{Y}_f) - H_f(\mathbf{Y}_f^{-i}))\right),\\ &= \left(-\sum_{f\in S_i\setminus S^*} w_f(H_f(\mathbf{Y}_f^{-i})) - \sum_{f\in S_i'\setminus S^*} w_f(H_f(\mathbf{Y}_f))\right)\\ &- \left(-\sum_{f\in S_i\setminus S^*} w_f(H_f(\mathbf{Y}_f)) - \sum_{f\in S_i'\setminus S_i} w_f(H_f(\mathbf{Y}_f^{-i}))\right).\end{aligned} \tag{24}$$

Hence,

$$u_i(S_i', S_{-i}) - u_i(S_i, S_{-i}) = \mathcal{P}(S_i', S_{-i}) - \mathcal{P}(S_i, S_{-i}). \tag{25}$$

Then, $\mathcal{P}(S_i, S_{-i})$ defined in (16) is an EPG of game Γ.

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