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Energy-efficient routing for correlated data in wireless sensor networks

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ABSTRACT

In this paper, we investigate the reduction in the total energy consumption of wireless sensor networks using multi-hop data aggregation by constructing energy-efficient data aggregation trees. We propose an adaptive and distributed routing algorithm for correlated data gathering and exploit the data correlation between nodes using a game theoretic framework. Routes are chosen to minimize the total energy expended by the network using best response dynamics to local data. The cost function that is used for the proposed routing algorithm takes into account energy, interference and in-network data aggregation. The iterative algorithm is shown to converge in a finite number of steps. Simulations results show that multi-hop data aggregation can significantly reduce the total energy consumption in the network.

1. Introduction

Wireless sensor networks (WSNs) consist of large numbers of sensor nodes where data from different nodes in a dense region may be highly correlated. For example, if the data are temperature measurements, the measurements are spatially and temporally correlated across the nodes. Transmitting all sensor data can increase traffic in the network and congestion at the destination nodes. This may result in higher energy consumption for the overall network. WSNs can reduce network traffic by aggregating data along the route from the furthest sensor node to the network sink.

Routing with data aggregation aims to find the optimum network topology for maximum correlated data gathering in order to reduce the cost function in resource-limited sensor networks. Most routing algorithms in WSNs aim to minimize the total transmission cost of transporting the data collected by nodes in a distributed manner. Taking into account data correlation as well as transmission energy per bit in making routing decisions can improve system performance in multi-hop WSNs. The data correlation between nodes can be exploited to reduce the amount of transmitted data which results in net energy savings. Routing decisions can significantly change when correlation awareness is introduced [1] and hence deserve careful study.

1.1. Related work

One of the most important metrics for WSNs is *energy-efficiency*. Energy-efficient routing algorithms allow WSNs to be deployed with smaller battery packs and to achieve longer lifetime for a given battery size [2,3]. There are mainly two ways to achieve energy-efficient route selection in WSNs: Minimum cost routing and maximum network lifetime routing. One classical energy-efficient routing algorithm for minimum cost routing is minimum energy routing (MER). The MER algorithm has been used to minimize the

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transmission energy in [4–7]. On the other hand, maximum lifetime routing, which aims to extending network lifetime by balancing traffic load is studied in [8–10]. Other energy-efficient routing algorithms focusing on energy-consumption as well as other metrics of network performance such as queueing delay, congestion or maximum data yield have been proposed [11,12]. Energy efficient routing algorithms subject to latency constraints are also investigated in [13].

In the context of wireless sensor networks, routing with data aggregation exploits data correlations along the multi hop path. Recent works have looked at exploiting the data correlation by using data aggregation along the multi-hop path [14–18]. In general routing algorithms with data aggregation fall into one of two categories: Routing-driven aggregation and aggregation-driven routing. In routing-driven algorithms, source data is routed through a specific path to the sink node (e.g. shortest path or minimum energy path depending on the application), data is aggregated opportunistically when data streams meet [14,19–22]. Most routing-driven algorithms use a full aggregation model, that is, all data packets received from child nodes are fully aggregated into one single packet at the parent node. This assumption may be practical for large scale WSNs where the correlation level between nodes vary significantly. In aggregation-driven routing algorithms [1,16,17], the route selected by each source node to the sink node is informed by the correlation between the data collected by the nodes. As data moves along the route, it is aggregated with data from sources on the route, reducing the traffic load at links closer to the sink. The reduction in the required bit rate resulting from aggregation affects the relative cost of each link. Thus, the route chosen by any source will not necessarily be the shortest or the minimum energy path to the sink.

Pattem et al. [18] construct an empirical data correlation model for a set of experimentally obtained data and investigate several tree construction schemes such as routing-driven aggregation, aggregation-driven routing and static cluster-based routing for WSNs. An empirical approximation is derived for the joint entropy of multiple sources and the cost function is proportional to the aggregated data in the network [18]. In our work, we use a cost function which additionally considers the energy consumption per symbol transmission and interference.

Several different coding schemes have been proposed in the literature that exploit data correlation. These schemes can be broadly categorized into two different data aggregation models: distributed source coding schemes (e.g. Slepian-Wolf coding model) and explicit side-information aggregation. Cristescu et al. [23] compare the performances of these two different data aggregation approaches. In the Slepian-Wolf coding model, the correlation between all nodes is completely known a priori at each source and is used to optimize the rate allocations of distributed aggregation algorithm. In this model, data is aggregated at each source in a distributed manner to achieve minimum joint entropy, and there is no further data aggregation at intermediate nodes. In [23], after obtaining *optimal rate allocation* using the Slepian-Wolf coding model, the shortest path tree (SPT) rooted at the sink is shown to be the optimal routing tree for the single sink data aggregation problem. However, distributed source coding has significant additional cost because of the a priori global knowledge assumption. Therefore, its implementation in a practical setting remains an open problem. In explicit side information aggregation, the data correlation between nodes is only exploited by receiving explicit side information from other child nodes. Explicit side information aggregation does not perform as well as source coding schemes because it does not consider the joint data correlation of multiple nodes [23].

The explicit side information data aggregation model can also be divided into two different aggregation models: single-input and multi-input aggregation models. In single-input aggregation model, the context of data aggregation is restricted. Data aggregation at an intermediate node depends only on the presence of side information provided by one other node connecting to it, and re-encoding is not allowed [16,17]. Under this model, Von Rickenbach and Wattenhofer [17] propose an optimal minimum energy gathering algorithm (MEGA) for *foreign coding* data aggregation model and an approximation algorithm called low energy gathering algorithm (LEGA) for *self coding* data aggregation model. In the foreign coding data aggregation model, once data is aggregated, it is not possible to alter the packet again in another node on the route, hence re-encoding is not possible. In the self-coding data aggregation model, data aggregation at an intermediate node does not depend on the quantity of the side information but only its availability. When there is side information connected to a source node, the entropy conditioning at nodes is fixed, it does not depend on the number of children nodes or the amount of side information available. The MEGA algorithm is based on the foreign coding model, it requires maintenance of two trees, the coding tree which is simply a directed minimum spanning tree for raw data and the SPT for aggregated data [17]. The LEGA algorithm on the other hand is based on the self coding model, it uses a shallow light tree as the data gathering algorithm and achieves a $2(1+\sqrt{2})$ approximation ratio. Although both MEGA and LEGA are optimal and near optimal approximation algorithms under their respective data aggregation models, their performance deteriorates in highly dense networks or in high correlation environments. This is because data correlation and redundancy among all nodes cannot be exploited efficiently. Each source node can only aggregate once, hence its redundancy with other nodes (other than the next hop node) cannot be eliminated.

In multi-input aggregation models, data aggregation is performed at a parent node only once data is received from all of its child nodes. The amount of aggregated data sent down the tree to the next hop from a particular node depends on the structure of the subtree rooted at that particular node. Therefore, an optimal tree structure minimizes the data rate (or encoding rate) as much as possible by maximizing the aggregation ratio at each intermediate parent node. The authors in [1,15,18] explore the effect of in-network aggregation at several hops using the multi-input data aggregation model. Unlike single-input data aggregation models, the proposed models allow data aggregation (or *data compression*) at several hops along a route allowing for reduced data traffic. Luo et al. [15] consider both the transmission cost and aggregation cost in selecting each

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node on the route. They use a multi-input data aggregation model which only requires that the output data aggregation amount is not less than any of the inputs and not more than the summation of all inputs. Moreover, the model does not depend on a specific data correlation model. Because of the generality of this model, we also adopt it for our analysis in this paper.

Energy efficient data aggregation problem through cooperative communications in WSNs was previously studied in the literature in [24,25]. These papers explore how data aggregation reduces power consumption by exploiting *cooperative communication* and using *spatial diversity*. However, cooperative communication aware routing increases overhead and often results in a high communication load that may offset the benefit of data aggregation. An application of recently developed *compressed sensing* to data collection in WSNs is studied in [26]. The authors aim to minimize network energy consumption through joint routing and compressed aggregation and propose fast near optimal solution techniques for practical use. However, this approach is generally more applicable for sparse data collection schemes rather than for correlation structure dependent data collection strategies.

Cristescu et al. [16] show that the problem of generating a data gathering tree with correlated data to minimize a general cost objective is NP-complete even for the simplifying assumption of a self-coding data-aggregation model. A simulated annealing based algorithm is proposed as the performance benchmark, since the algorithm to construct the optimal routing solution is NP complete. The optimal solution is conjectured to be a trade-off between the SPT and the solution to the traveling salesman problem. Different heuristic approximation algorithms are studied to construct correlated data gathering trees and compared to the simulated annealing based algorithm.

1.2. Our contributions

In correlated data gathering problems, the transmission structure and aggregated data rate at each node are coupled. For example, if distributed source coding schemes such as the Slepian-Wolf coding model are used, finding the optimal route becomes simple, it is usually the shortest or minimum energy path. However, if a multi-hop data aggregation model is used in WSNs, which is the case in this paper, the transmission structure will affect the aggregated data rate at each node. Therefore, the routing problem becomes more complicated and in this case the total cost minimization problem is NP-complete [16].

Data gathering with correlated sources using a partial data aggregation model (i.e. varying traffic load at each node depending on the tree structure) and interference management for routing algorithms in wireless links are usually studied separately in the context of WSNs [16,20,27]. One of the contributions of this paper is to incorporate correlation and interference awareness into the total network energy minimization problem. Most routing schemes previously proposed in the literature for correlated data aggregation in WSNs do not incorporate the effect of wireless interference. Aside from the transmission energy metric, interference and correlation awareness performance metrics also significantly affect routing decisions. For example, when interference at the next hop is high and the amount of data cannot be reduced significantly along that node's path to the sink node, a node may not utilize that next node since the cost of using that path becomes too high. Therefore, constructing optimal transmission structures without considering the interference associated with wireless channels may lead to infeasible solutions. To prevent this, an optimal energy minimizing routing algorithm should *jointly* optimize energy, interference and data correlation.

Game theoretic formulations of communication problems in WSNs lead to the construction of algorithms which exploit the distributed decision making capability of each sensor node to improve or optimize network-wide performance. In this paper, we propose a simple game-theoretic model using congestion game definitions to minimize the total energy consumption in the network. While energy-efficient routing in WSNs has been studied extensively, our approach and solution formulation are significantly different from the previous work cited above. Firstly, our work differs from prior work by jointly considering the energy metric, interference awareness and opportunity for *multi-hop* partial data aggregation. To the best of our knowledge, no previous work exists that simultaneously considers the correlated data gathering problem with these measures, especially when a game theoretical strategy is employed to obtain a *distributed algorithm* to solve the optimization problem. Secondly, our work differs from previous potential and congestion routing game formulations by incorporating a general multi-hop data aggregation model into the problem definition to describe data reduction in congestion games.

In our previous work [1], we have addressed correlation awareness within the congestion game framework. This approach has been extended in this paper. Compared to our previous results [1], the data aggregation method used in this paper utilizes a more general model which is applicable for a variety of data aggregation (or compression) schemes, and proposes an *effective* energy gain metric as the performance benchmark for fair comparisons with other classical approaches in the literature.

The rest of the paper is organized as follows: In Section 2, the system and data aggregation models are defined. An efficient routing framework for energy minimization is proposed in Section 3. Section 4 presents different facility cost selection choices for the congestion game and shows the convergence of the proposed algorithm. In Section 5, we present numerical results. Finally, Section 6 presents concluding remarks and future work.

2. System model

Our focus is on applications where joint data aggregation and routing is desirable for data gathering in WSNs. For example, images collected by different sensor nodes in a video surveillance and image based tracking systems, or environmental data measurements such as temperature, humidity, vibration, sound or light from a field of sensors are possible application scenarios.

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We consider the problem of maximum correlated data gathering with a single sink, which is the destination node for all data. All source nodes in the network collect, transmit and aggregate data. The total number of source nodes is N. Let $\mathcal{N}$ be the set of all nodes, comprised of source nodes and one sink node, and $\mathcal{E}$ be the set of edges, or possible directed links among nodes. An edge is assumed to exist between two nodes if they are within communication range. Define the network graph $\mathcal{G} = (\mathcal{N}, \mathcal{E})$. Let $|A|$ denote the number of elements of set A. Then $|\mathcal{N}| = N + 1$, and $|\mathcal{E}| \leqslant N(N+1)$. The sources are labeled Y_1 through Y_N. For simplicity, we assume there is only a single sink labeled D which collects data from all the nodes. The algorithm proposed in this paper can be extended to the case where there are multiple sinks and data from different subsets of nodes has to be sent to different sinks. All nodes are randomly distributed over a specified region.

Let (Y_k, Y_l) denote the communication link, or edge, from node Y_k to node Y_l. We define $V_{k,l}$ to be a binary random variable which is 1 if a communication link has been established between from Y_k to Y_l, and 0 otherwise.

In the following, we develop an algorithm that minimizes the total network energy consumption to route all sensor data to the sink node. The route for node Y_i on graph $\mathcal{G} = (\mathcal{N}, \mathcal{E})$ is an ordered list of nodes over which data from node Y_i will traverse to reach the sink node D: $S_i = (Y_0, Y_1, Y_2, \ldots, Y_{U-1}, Y_U)$ where Y_0 is node Y_i and Y_U is the sink node D. Any two consecutive nodes on a route communicate across an active link. The set of links comprising path S_i is link $(S_i) = \{(Y_i, Y_1), (Y_1, Y_2), \ldots, (Y_{U-1}, D)\}$. Every link on the route must be a directed edge in graph $\mathcal{G}$, $(Y_k, Y_{k+1}) \in \mathcal{E}$ for $k = 0, 1, \ldots, U$. The set of all possible routes for node Y_i is $\mathbb{X}_i$.

We assume that there is a target bit error rate (BER) which ensures successful communication across a link. We assume that our system has perfect error detection but no error correction capability. Automatic retransmission request is used so that a packet with error is retransmitted until received correctly. Suppose that the packet length is M. Then the probability of correct reception of the packet is $P_c(\gamma) = (1 - 2BER(\gamma))^M$ where $BER(\gamma)$ is bit error rate corresponding to a signal to interference and noise ratio (SINR) γ. The $BER(.)$ function will depend on the modulation scheme and the noise and interference environment. In this paper, we assume a CDMA system, for which cumulative interference can be assumed to be Gaussian (note that CDMA assumption is not essential for the proposed algorithm, but serves as a simple illustrative example). We use non-coherent frequency shift keying modulation for which $BER(\gamma) = 0.5\ \exp\ (-0.5\gamma)$ under Gaussian noise and interference. This equation can be used to find a target SINR γ^* for the system.

Our system uses synchronous direct-sequence CDMA where nodes use variable spreading sequences. The spreading factor for each transmitter, L, can be adjusted to meet the target quality-of-service (or target SINR) requirements. The minimum spreading gain between the nodes Y_i and Y_j to reach a certain target SINR, γ^*, is [28]

$$L_{i,j} = \frac{\gamma^* \left[\sum_{k=1, k \neq i,j}^{N} h_{k,j} P_k \right]}{h_{i,j} P_i - \gamma^* \sigma^2}, \tag{1}$$

where the link gain $h_{i,j} = 1/d_{i,j}^p$, $d_{i,j}$ is the distance between the nodes Y_i and Y_j, p is the path loss exponent, which is usually between 2 and 4 for free-space and short-to-medium-range radio communication and σ^2 is the thermal noise power. The transmission rate, or bit throughput between nodes Y_i and Y_j in bits-per second (bps) is determined by the spreading rate $L_{i,j}$: $\Omega_{i,j} = W/L_{i,j}$ where W is the system bandwidth.

The energy per bit, which has units of Joule/bits, represents the total amount of energy consumed in order to deliver one data bit to the destination. This paper considers only the energy used for transmission, neglecting the energy used for reception and data processing. The energy per bit $E_b^{i,j}$ for packet transmissions between nodes Y_i and Y_j can be defined as in [28]:

$$E_b^{i,j} = \frac{MP_i}{m \Omega_{i,j} P_c(\gamma)}, \tag{2}$$

where M is the packet length, m is the number of information bits in a packet, P_i is the constant transmit power for all Y_i, $i = \{1, 2, \ldots, N\}$.

To quantify the amount of data generated by each sensor node and data aggregation along the route, sources are associated with their data rates or weights as defined in [15]. It is assumed that data collected by the sensor nodes is correlated over geographical regions. Therefore, depending on the density of the sensor nodes in the field, the readings from nearby nodes may be highly correlated and hence contain redundant data. Each source node Y_i generates data at a certain rate $\Psi(Y_i)$, where $\Psi(Y_i)$ is referred to as the data rate of source Y_i. It is important to note that the data rate $\Psi(Y_i)$ refers to rate of symbol encoding rate of source Y_i, not the rate of data transmission. The data rate $\Psi_i(Y_i)$ shows the average number of bits per symbol used to encode the data source and has units bits/symbol. As shown in Fig. 1, the source nodes represented with circles in the network can either send their own raw data directly to the sink, or if they relay traffic for other sources, they may aggregate their data with data from those sources. The objective of our routing solution is to minimize the energy expenditure per useful information bit transmitted to the sink. We consider a bit that carries new information with no redundancy to be a useful bit.

2.1. Data aggregation model

In this paper, correlated data from multiple nodes is aggregated into one compressed data stream in order to reduce the network load. For data aggregation, we adopt the lossless step-by-step multi-hop aggregation model introduced in [15]. In this approach, each source node aggregates its data with that of its child nodes in a step-by-step fashion. Let $\Psi(Y_i)$ denote the rate of data generated by node Y_i. Let $\mathbf{Y}_i$ be the set of node Y_i and all child nodes of node Y_i. Define $\Psi_i(\mathbf{Y}_i)$ as the net data rate at node Y_i due to data generated by node Y_i and its child nodes, after the aggregation process is completed. For instance, suppose that node Y_i has q child nodes $Y_1, Y_2, \ldots, Y_q$. Then $\mathbf{Y}_i = \{Y_i, Y_1, Y_2, \ldots, Y_q\}$. The data received from a child node Y_k, $k = 1, \ldots, q$ will be data aggregated from node Y_i and all of its child nodes, $\Psi_i(\mathbf{Y}_i)$. If Y_i is a

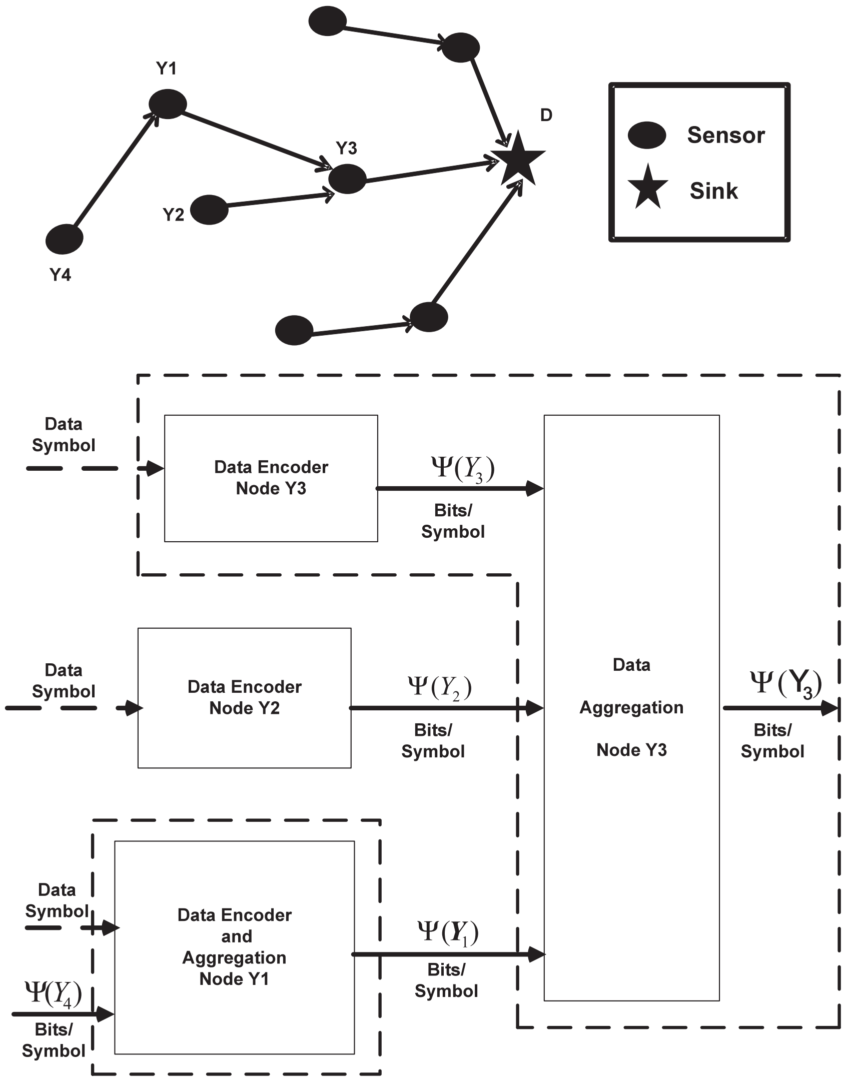

Fig. 1. An example of data gathering tree. Data generated by the encoder of each source node arrives at sink D after data aggregation through intermediate source nodes.

leaf node with no child nodes, then it will forward only data generated by itself, $\Psi_i(\mathbf{Y}_i) = \Psi(Y_i)$.

The aggregation of q multiple inputs with source node Y_i is performed sequentially, that is, incoming data is aggregated with existing data in order of arrival, and data transmission takes place after data from all child nodes has been received and aggregated. For example in Fig. 1, it can be assumed that node Y_3 receives data from node Y_2 before it receives data from node Y_1 because Y_2 has no subtree and does not perform aggregation before sending its data. So node Y_3 first aggregates data from node Y_2 with its original data. Node Y_3 saves this intermediate aggregated data, which has data rate $\Psi^{temp}(Y_3)$; node Y_3 will aggregate the data again with the data from node Y_1 when that data arrives and send the final result with data rate $\Psi_3(\mathbf{Y}_3)$, along its path for possible further aggregation along the route to sink D. At the end of the aggregation process, the data rate of node Y_3 becomes $\Psi_3(\mathbf{Y}_3)$. Multi-hop data aggregation as illustrated above is repeated at every intermediate source node along the route.

The multiple data inputs to a node are aggregated sequentially rather than jointly, as seen with the differential entropy model [23] because storing multiple sources' data and aggregating them at once requires more memory and power for sensors. The data reported from different nodes will arrive at the parent node at different times due to intermediate nodes' signal processing, distance between nodes, wireless medium characteristics, error-control schemes, interference, noise or transmitted powers. With a sequential aggregation scheme, data from early nodes may be processed and deleted before data from later sources arrives, saving memory. Further, joint processing of data is likely to be more efficient but also more computationally intensive. Joint aggregation may be beyond the capabilities of a wireless node or may require significantly more computational time and processing power.

Let $\Psi^{temp}(Y_i, Y_j)$ be the temporary data rate of a node after data generated by node Y_i is aggregated with data from one of its child nodes Y_j. This data rate is calculated as [15]:

$$\Psi^{temp}(Y_i, Y_j) = \max(\Psi(Y_i), \Psi(Y_j)) + (1 - \rho_{i,j}) \times \min(\Psi(Y_i), \Psi(Y_j)), \quad (3)$$

where $\rho_{i,j}$ is the correlation coefficient between nodes Y_i and Y_j. Similar to [15], in order to distinguish between the correlation between the raw data generated by two nodes and the correlation between the aggregated data calculated at those nodes, we use a "forgetting" factor for aggregated data. The correlation between aggregated data at two parent nodes is only a fraction of the data correlation calculated according to their distance. Note that the above aggregation model is not a necessary element for the proposed algorithm in this paper. The proposed algorithm can be readily adapted for use with any other multi-hop data aggregation model.

3. Efficient routing framework for energy minimization

3.1. Energy per symbol and symbol throughput

The energy consumption per symbol transmission of a node depends on the data rate of the node and the transmission energy per bit. Given the correlation models in Section 2.1, the energy used per symbol transmitted between nodes Y_i and Y_j, accounting for data redundancy through correlation, can be defined as

$$E_s^{i,j}(\Psi_i(\mathbf{Y}_i)) = E_b^{i,j}\left[\frac{\text{Joule}}{\text{bits}}\right]\Psi_i(\mathbf{Y}_i)\left[\frac{\text{bits}}{\text{symbol}}\right], = \frac{MP_i}{m\ \Omega_{i,j}\ P_c(\gamma)}\Psi_i(\mathbf{Y}_i)\left[\frac{\text{Joules}}{\text{symbol}}\right], \quad (4)$$

where $\Psi_i(\mathbf{Y}_i)$ is the aggregated data rate at node Y_i and $\mathbf{Y}_i$ is the set of all q sources using node Y_i including Y_i, i.e. $\mathbf{Y}_i = \{Y_i, Y_1, Y_2, \ldots, Y_q\}$. The required energy per symbol has units Joules/symbol and indicates the total amount of energy consumed to correctly deliver one data symbol to the destination.

Similar to the definition of energy per symbol, the symbol throughput of a link between nodes Y_i and Y_j is defined as

$$\zeta_{i,j}(\Psi_i(\mathbf{Y}_i)) = \frac{W}{L_{i,j}}\left[\frac{\text{bits}}{\text{second}}\right]\frac{1}{\Psi_i(\mathbf{Y}_i)}\left[\frac{\text{symbols}}{\text{bit}}\right] = \frac{\Omega_{i,j}}{\Psi_i(\mathbf{Y}_i)}\left[\frac{\text{symbols}}{\text{second}}\right]. \quad (5)$$

The symbol throughput has units symbols/s (sps) and represents the total number of symbols transmitted per second to the destination.

In a communication network, the link with the least symbol throughput among all links on a route determines the symbol throughput of that route. Then the symbol throughput of source Y_i is defined as the minimum of the symbol throughput of all links on the route from source Y_i to the data sink D on its route. Hence, we define the symbol throughput of source Y_i, when route $S_i \in \mathbb{X}_i$ is selected, to be

$$\lambda_i = \min_{\forall (Y_k, Y_l) \in \text{link}(S_i)} \zeta_{k,l}. \quad (6)$$

For the data aggregation model being considered, the bottleneck throughput of nodes that are connecting to sink via the same node is the same and is equal to the minimum of all bottleneck throughput for all nodes whose paths are connected to sink via that same node.

3.2. Optimization problem

We want to find a tree structure on the network graph that will minimize the total energy consumption in the network. This leads to the question of how to construct *efficient data gathering trees* in the network. The energy minimization problem in the network and physical layers can be formulated as follows:

$$\min_{\substack{S_i \in \mathbb{X}_i \\ i=1,\ldots,N}} \sum_{i=1}^{N} \sum_{\forall (Y_k, Y_l) \in \text{link}(S_i)} E_s^{k,l}(\Psi_k(\mathbf{Y}_k)), \quad (7a)$$

$$\text{subject to } \text{SINR}_{k,l} \geqslant \gamma^*, \quad \forall (Y_k, Y_l) \in \text{link}(S_i), \ \forall Y_i \in \mathcal{N}, \quad (7b)$$

$$P_i = C, \quad \forall Y_i \in \mathcal{N}, \quad (7c)$$

$$0 \leqslant \zeta_{k,l}(\Psi_k(\mathbf{Y}_k)) \leqslant B, \quad \forall (Y_k, Y_l) \in \text{link}(S_i), \ \forall Y_i \in \mathcal{N}, \quad (7d)$$

$$\sum_{\forall Y_l \in N} V_{k,l} = 1 \quad \forall Y_k \in \mathcal{N}, \quad (7e)$$

$$V_{k,l} = \begin{cases} 1, & \text{if } \exists Y_i : (Y_k, Y_l) \in \text{link}(S_i), \\ 0 & \text{otherwise}. \end{cases} \quad (7f)$$

In the above formulation, $\mathbf{Y}_l$ is the set of all sources connected directly into node Y_l and including node Y_l. Constraint (7b) represents the quality-of-service requirement of each node where $\text{SINR}_{k,l}$ is the received SINR at node Y_l for the link between nodes Y_k and Y_l, constraint (7c) represents the constant transmit power constraint $P_k = C$ for all nodes Y_k, $k = \{1, 2, \ldots, N\}$, constraint (7d) limits the flow on each link to be less than the wireless link capacity B, constraint (7e) requires that each source must have exactly one outgoing link.

The optimum routing solution is hard to determine when each sensor uses the data aggregation model in Section 2.1 since multi-hop aggregation is employed along each route. The joint optimization of transmission cost and data aggregation is shown to be NP-complete even for the simplifying assumption of a self-coding data aggregation model [16]. Finding the energy minimizing route is an NP-hard optimization problem. The solution we propose is a decentralized energy minimization algorithm using the correlation structure of the network. We introduce a game theoretic formulation which is shown to converge to a local optimal solution with relatively low complexity and in a distributed fashion.

3.2.1. Game theoretic interpretation

In this section the above optimization problem is formulated as a congestion game which is shown to be isomorphic with a potential game. In this game, the players are the source nodes in quest of routes, the source nodes used throughout the route are the shared facilities, the actions of the players are the selection of a group of facilities that form a route to the sink. Every route selected has an associated cost.

Formally, the proposed game-theoretic routing model for correlation aware routing models route selection as a congestion game Γ on graph $\mathcal{G} = (\mathcal{N}, \mathcal{E})$ [29]. The game Γ is defined as a tuple $(\mathcal{N}, \mathcal{F}, (\mathbb{X}_i)_{i\in\mathcal{N}}, (w_f)_{f\in\mathcal{F}})$ where $\mathcal{N} = \{Y_1, \ldots, Y_N\}$ denotes the set of players, i.e. the source nodes in our game, $\mathcal{F} = \{1, \ldots, m_f\}$ denotes the set of facilities. Let $\mathcal{T}$ denote a routing tree rooted at the sink node D comprised of edges in graph $\mathcal{G}, \mathcal{T} \subset \mathcal{E}$. Node Y_i cannot connect to node Y_j if it is already connected to it, i.e. if link $(Y_j, Y_i) \in \mathcal{T}$, then $(Y_i, Y_j) \notin \mathcal{T}$. Let $\mathbb{W}_i = \{Y_j \in \mathcal{N} \setminus Y_i \mid (Y_j, Y_i) \in \mathcal{T}\}$ denote the set of all nodes in the subtree rooted at node Y_i for the given graph $\mathcal{G}$ and let $\mathbb{X}_i = \{Y_i, Y_j, \ldots, D \mid Y_j \in \mathcal{N} \setminus \{\{Y_i\} \bigcup \mathbb{W}_i\} \wedge (Y_i, Y_j) \in \mathcal{E}\} \subseteq 2^{\mathcal{F}}$ denote the set of $N - 1 - |\mathbb{W}_i|$ routes corresponding to nodes to which Y_i may send its data, i.e. the strategy space of player Y_i. Since in our problem statement each node can only send data to one node in the network, and every node is a player in the game, once node Y_i's data reaches node Y_j, it will follow the path selected by node Y_j. Define $\mathbf{S}_G = (S_1, \ldots, S_N) = (S_i, S_{-i})$ as the *state of the game* for the given graph G in which player Y_i chooses strategy $S_i \in \mathbb{X}_i$ where $S_{-i} = (S_1, S_2, \ldots, S_{i-1}, S_{i+1}, \ldots, S_N)$ is the strategy space of player Y_i's opponents. The strategy S_i of a node Y_i is to select a link from the available strategy space $Y_j \in \mathbb{X}_i$. Once the first link on the route is selected, Y_i's data must follow the path selected by node Y_j.

For our application, a source node is also a facility f, which aggregates data. $w_f : \mathbb{N} \to \mathbb{R}$ is a cost function associated with using the facility f. We define $\theta_f(S_i, S_{-i})$ as the subset of *sources* directly connected to facility f including the source node at facility f, that is $\theta_f(S_i, S_{-i}) = \{Y_i | f \in S_i\}$. The players aim to choose strategies $S_i \in \mathbb{X}_i$ minimizing their individual cost, where the cost $\delta_i(S_i, S_{-i})$ of player Y_i is given by $\delta_i(S_i, S_{-i}) = \sum_{f\in S_i} w_f(\theta_f(S_i, S_{-i}))$. We define the utility function for source Y_i in our congestion game as

$$\begin{aligned} u_i &: \mathbb{N} \to \mathbb{R},\ u_i(S_i, S_{-i}) = -\delta_i(S_i, S_{-i}), \\ &= -\sum_{f\in S_i} w_f(\theta_f(S_i, S_{-i})). \end{aligned} \tag{8}$$

The performance of the game is influenced by the cost function $w_f(\theta_f(S_i, S_{-i}))$ selected for use of the facilities. We propose and compare several metrics in the next section.

4. Facility cost selection for the congestion game

We consider the problem of constructing the *minimum energy correlated data gathering tree*. In setting up the costs for facilities, we consider the following parameters:

1. The energy spent on relaying bits or symbols from the facility on outgoing links,
2. The opportunity for aggregation.

4.1. Minimum energy routing

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

$$u_i(S_i, S_{-i}) = -\sum_{f\in S_i} E_b^f, \tag{9}$$

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

4.2. Correlation-aware routing for energy minimization

In WSNs, constructing the correlated data gathering route is an important task for cost minimization [16,23]. We propose a correlation-aware routing (CAR) game formulation to solve the energy per symbol minimization problem in (7a). This formulation accounts for data correlation across nodes and the potential for data aggregation in the network. For CAR, given a network, the problem is to form a maximal correlated data aggregation tree from each reporting sensor (source) to the sink. For CAR, we define the cost of using facility f

$$\begin{aligned} w_f(\Psi_f(\theta_f(S_i, S_{-i}))) &= E_b^f \Psi_f(\theta_f(S_i, S_{-i})), \\ &= E_s^f(\Psi_f(\theta_f(S_i, S_{-i}))), \end{aligned} \tag{10}$$

where $\Psi_f(\theta_f(S_i, S_{-i}))$ is the total aggregated data rate at facility f. The utility function $u_i(S_i, S_{-i})$ of source Y_i is given by

$$\begin{aligned} u_i(S_i, S_{-i}) &= -\sum_{f\in S_i} \Big(w_f(\Psi_f(\theta_f(S_i, S_{-i}))) - w_f(\Psi_f(\theta_f^{-i}(S_i, S_{-i}))) \Big), \\ &= -\sum_{f\in S_i} E_b^f \Big[\Psi_f(\theta_f(S_i, S_{-i})) - \Psi_f\Big(\theta_f^{-i}(S_i, S_{-i})\Big) \Big], \end{aligned} \tag{11}$$

where $\Psi_f\Big(\theta_f^{-i}(S_i, S_{-i})\Big)$ is the total aggregated data rate at facility f when source Y_i is not present. When Y_i is not present on facility f, all the sub-trees rooted at Y_i are pruned because we are interested in the correlation contribution of node Y_i (see Fig. 2). Each player aims to choose the strategy $S_i \in \mathbb{X}_i$ to maximize its utility function so as to find the best routes that will result in maximum data aggregation.

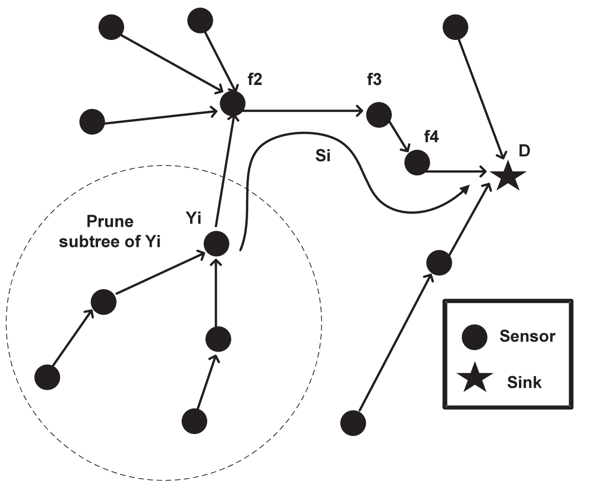

Fig. 2. Pruning of the subtree rooted at Y_i to calculate $\Psi_f(\theta_f^{-i}(S_i, S_{-i}))$ over facilities $\{Y_i, f_2, f_3, f_4\} \in S_i$.

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4.2.1. Potential game formulation for CAR

In analyzing game performance, we look for a Nash equilibrium (NE) solution, which represents a stable state in which no player can unilaterally improve its utility by changing its strategy. In certain classes of games it can be shown that the game converges to a NE when a *best* or *better response* adaptive strategy is employed. In what follows, we show that the congestion game associated with CAR is isomorphic with a potential game, for which a best response strategy is shown to converge to a NE. More specifically, we can show that games defined within these algorithms are exact potential games, by defining an exact potential function which is the optimization target minimization of 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 a unilateral deviation by the player is reflected in a global function. We assume that in the normal form game each player takes actions sequentially and at each stage of the game players choose actions which improve their utility functions. Some of the properties of potential games are:

- All NE points are the maximizers of the potential function, either locally or globally,
- Potential games have at least one pure NE,
- At each step of the potential game, a *better response* or *best response* strategy converges to a NE if each player investigates its strategy space and takes actions to maximize its utility [30,31].

An exact potential game is a special case of a potential game. A game that has an exact potential function is called an exact potential game. An exact potential function $\mathcal{P}(.)$ is defined as

$$\mathcal{P}:\mathbb{X}_1\times\ldots\times\mathbb{X}_N\to\mathbb{R},\ \text{and}\ S_i,S_i'\in\mathbb{X}_i\ \forall i\in\mathcal{N},\\ u_i(S_i,S_{-i})-u_i(S_i',S_{-i})=\mathcal{P}(S_i,S_{-i})-\mathcal{P}(S_i',S_{-i}). \tag{12}$$

The above result shows that the gain (loss) caused by any players unilateral move is exactly the same as the gain (loss) in the potential function, which can be a global objective function. We will demonstrate that correlation aware routing with utility functions given by (11) is an exact potential game (EPG) with the exact potential function,

$$\mathcal{P}(S_i,S_{-i})=-\sum_{f=1}^{m_f}w_f(\Psi_f(\theta_f(S_i,S_{-i}))), \tag{13}$$

where m_f is the total number of facilities used in the directed graph $\mathcal{G}$ and $m_f = N$ since all nodes are used as a facility in the network.

Theorem 1. *CAR defined by utility function (11) and the potential function (13) is an EPG.*

Proof. See Appendix A. □

Corollary 1. *CAR always has a NE and converges to a NE solution by using a best response adaptive strategy.*

Corollary 2. *Any NE of CAR is locally optimal, i.e. in a NE, all the players cannot reduce the energy unilaterally and thus the game reaches a local minimum total energy for CAR.*

In the CAR algorithm, each source $Y_i\in\mathcal{N}$ updates its strategy S_i so as to maximize of its corresponding utility (11). Hence, in each iteration, each user finds the best routes (sequential updates) that will increase its utility. From Theorem 1, the potential function $\mathcal{P}(S_i,S_{-i})$ will continue to increase until it reaches a local maximum point using best response dynamics. Since the potential function of any strategy profile is finite, it follows that every sequence of improvement steps and the number of iterations to converge is finite due to the finite improvement property (FIP) of best response dynamics in congestion games [30,32].

The procedure for sequential updates of routes (i.e. Gauss–Seidel approach [33]) with best response dynamics of CAR can be summarized as follows:

Input: A connected network $\mathcal{G}=(\mathcal{N},\mathcal{E})$.
Output: A new energy minimizing and correlation aware data gathering tree G'.
Initialization: Construct an initial spanning tree (For example, we use MER using the distributed Dijsktra's algorithm [34] as the initial spanning tree). Then, use the following iterations for iterative correlation aware energy minimization.
Repeat: At each iteration $n + 1$ ($n = 1, 2, 3, \ldots$):

- For each of the source node Y_i, $i\in\{1, 2, \ldots, N\}$:
  - (a) Node Y_i engages in pairwise negotiations with other nodes in $\mathcal{N}\setminus\{\{Y_i\}\bigcup\mathbb{W}_i\}$ with which it is connected in graph $\mathcal{G}$, investigates the utility (11) associated with all possible paths.
  - (b) Node Y_i selects the best response strategy $S_i\in\mathbb{X}_i$ that maximizes the utility (11). During best response, node Y_i updates its strategy (route).

Until: The stopping criteria $\varDelta$ is met.

The stopping criterion $\varDelta$ is the minimum number of iteration steps κ for the algorithm to converge (i.e. when the total energy in the network between subsequent iterations is smaller than ϵ where ϵ is a prescribed tolerance value), where κ is a counter which adds one after each updating process. The total network energy consumption per symbol transmission for the CAR algorithm is

$$E_s^{total,CAR}=\left(\sum_{f=1}^{m_f}w_f(\Psi_f(\theta_f(S_i,S_{-i})))\right). \tag{14}$$

The total symbol throughput in the network is the symbol throughput of sum of bottleneck throughput of each source, i.e.

$$\zeta^{total}=\sum_{i=1}^{N}\lambda_i, \tag{15}$$

where λ_i is defined in (6).

Constructing the initial spanning tree can require significant computational effort. However since the algorithm performs iterative updates, starting from a better initial tree structure will result in closer optimal results at the final iteration. In simulations, the algorithm with was initialized with the minimum energy routes (MER) instead of shortest path tree (SPT). It was found that starting with MER gave better results at the end compared to SPT. Starting with a star topology structure, where every node sent data directly to the sink node yielded even worse results on average.

This algorithm requires information to be exchanged between neighboring nodes in the network. In order to calculate the utility function in (11), each node has to know the utility function of every potential next hop. The utility of every potential route is calculated by adding the energy consumption of forwarding to next hop node and the utility function of next node.

One of the primary drawbacks of most best response strategies like the CAR algorithm introduced here, is the computational complexity, which is $O(N^2)$ for each iteration, where N is the network size after the construction of the initial spanning tree using Dijkstra algorithm. (Note that the worst case computational complexity of MER using Dijkstra algorithm is $O(N^2)$ [35].) However, the computational complexity of the original congestion game formulation in Section 3.2.1 is $O(2^N)$ since $m_f = N$. To address this issue, for large network sizes, the search for better routes can be restricted on k-hop neighborhood nodes $\mathcal{B}_k(Y_i)$ of each source node Y_i in order to reduce the computational complexity. This is based on the observation that a node is highly correlated within a certain radius of its neighborhood. This is a natural assumption for sensor networks, since the correlation decreases as the distance between nodes increases, hence the local correlation is dominant. Implementing a better response algorithm instead of the best response will result in a significant reduction in complexity, at the expense of convergence speed. Moreover, there may be multiple NE in a potential game and the performance of different equilibria may vary.

4.3. Minimum Energy Data Gathering Algorithm (MEGA)

In the *foreign coding* aggregation model, once aggregated data is not aggregated again at subsequent facilities. Therefore, after data aggregation, the best strategy is for a node sending its data to the sink is to transmit the aggregated data over the minimum energy route. MEGA is an algorithm that tries to minimize the aggregated and raw data costs jointly [17]. The resulting topology is a combination of two tree constructions, namely the coding tree and SPT (or in our results MER tree). The coding tree is for the aggregation of the raw data and the MER (or SPT) tree is for the aggregated data (see Fig. 3). Let us define the set of facilities used for the MER tree of node Y_i as M_i and coding tree as S_i. Hence, the strategy of each source node S_i is to select the best possible next hop to aggregate more. With foreign coding data aggregation model, the utility function of MEGA is

$$u_i(S_i, S_{-i}) = -E_b^{i,j}\Psi_i(Y_i) - [(1-\rho_{i,j})\Psi_i(Y_i)]\sum_{f\in M_j} E_b^f, \tag{16}$$

where $\rho_{i,j}$ is the correlation coefficient between nodes Y_i and Y_j and $Y_j \in S_i$, i.e. the next node of the coding tree of node Y_i. In other words, MEGA tries to find the next hop Y_j that minimizes total energy consumption over the coding tree S_i. Note also that $M_j \subseteq S_i$.

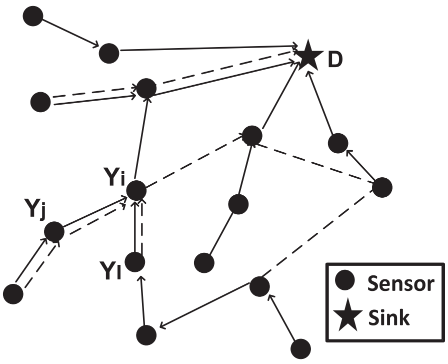

Fig. 3. Multiple transmissions using two different links from node Y_i in MEGA. The coding tree is shown with dashed arrows and the MER tree is with solid arrows.

After constructing the coding trees according to utility function of (16) for MEGA, the total energy per symbol consumption in the network is

$$E_s^{total,MEGA} = \sum_{i=1}^{N}\left(E_b^{i,j}\Psi_i(Y_i) + \left(\left[(1-\rho_{i,j})\Psi_i(Y_i)\right]\sum_{f\in M_j} E_b^f\right)\right). \tag{17}$$

The symbol throughput of each source Y_i is calculated as the minimum throughput of multi-hop links from each source to the sink. The links of each source Y_i consists of the links in the coding tree S_i. Therefore, the symbol throughput of source Y_i is given in (6) and the total symbol throughput in the network is given in (15).

4.4. Energy and delay trade-off

Most sensor network applications are sensitive to data delay. Energy and delay are competing objectives that cannot be minimized simultaneously. The trade-off between energy consumption and data delay has been well documented in the literature [36–40]. In a lightly loaded network, direct single hop transmission across the network will yield the shortest possible delay but use the most energy. Adding one or more intermediary hops to the link will cause additional delay but will reduce the total transmission energy required. In practical wireless sensor networks, delay can be influenced by a variety of factors such as the number of links aggregating at each node, channel characteristics and retransmission schemes. Taking into account all these factors and based on prior work we expect that the longer routes constructed by the proposed CAR algorithm would yield longer delays compared to other algorithms like SPT or MER. A quantitative analysis of the energy-delay tradeoffs is a subject of future work.

5. Simulation results

In this section, we present an extensive set of numerical results to evaluate the performance of our proposed CAR

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algorithm in comparison to the other classical approaches, MER and MEGA. For MER and CAR algorithms, the data generated by each source is aggregated at multiple nodes throughout the route to the sink using the aggregation model in Section 2.1. For nodes randomly deployed in a 2*D* field, the impact of network size, correlation coefficient and number of iterations required to converge for different algorithms are compared. The performance of our proposed CAR algorithm is compared in terms of improvements in energy savings with MER and MEGA.

For a fair comparison of all algorithms, the total network energy per symbol is compared under a constant total symbol throughput $\zeta^{total} = \sum_{i=1}^{N} \lambda_i$ requirement. In other words, the total *effective* energy per symbol of all algorithms is compared for a given information throughput. Therefore, using this metric, the energy and throughput gains are incorporated into one performance metric measuring *effective* energy improvements.

5.1. Simulation setup

The number of sensor nodes in the network is varied from $N = 10$ to $N = 40$, the sensors are uniformly distributed over a square area of dimension 40 m $\times$ 40 m. We adopt the *Gaussian random field* data correlation model that is frequently encountered in practice [23]. In this model, correlation coefficient $\rho_{i,j}$ between nodes Y_i and Y_j decreases exponentially with the increase of the distance between nodes $d_{i,j}$, i.e. $\rho_{i,j} = \exp\left(-d_{i,j}^2/c\right)$ where c is the correlation constant where $c = 0\ \mathrm{m}^2$ corresponds to no correlation, $c = 100\ \mathrm{m}^2$ corresponds to low correlation and $c = 1000\ \mathrm{m}^2$ corresponds to high correlation environment. We select the path loss exponent to be $p = 2$. In simulations, we use a "forgetting" factor of 0.8 per link, that is, if data is aggregated at a node Y_i, then the correlation $\rho_{i,j}$ between that node's aggregated data and its parent node Y_j in the routing tree is reduced to 0.8 of its original value. The noise power is $\sigma^2 = 10^{-13}$ Watts, which corresponds to thermal noise power for a bandwidth of $W = 1$ MHz. We choose the equal transmit powers of all nodes to be 110 dB above the noise floor ($P_i = 10^{-2}$ Watts, $\forall i \in \mathcal{N}$). The target SINR is selected to be $\gamma^* = 5$ (7 dB). We assume that each packet contains 80 bits of information and no overhead (i.e., $m = M = 80$). The generated raw data rate of each source, $\Psi(Y_i)$, is assumed to be constant for all $Y_i \in \mathcal{N}$ and without loss of generality, each symbol is represented with 1 bit of information, i.e. $\Psi(Y_i) = 1$ bits/symbol. The total effective energy consumption of all algorithms are compared when the required symbol throughput is $\zeta^{total} = 100$ kbps. The results are simulated and averaged over 100 different network configurations for each routing algorithm.

The MER algorithm uses Dijkstra's algorithm to find the best routes from sink to source nodes with one iteration. Although MER was not proposed in the context of data aggregation, we set-up the paths according to their

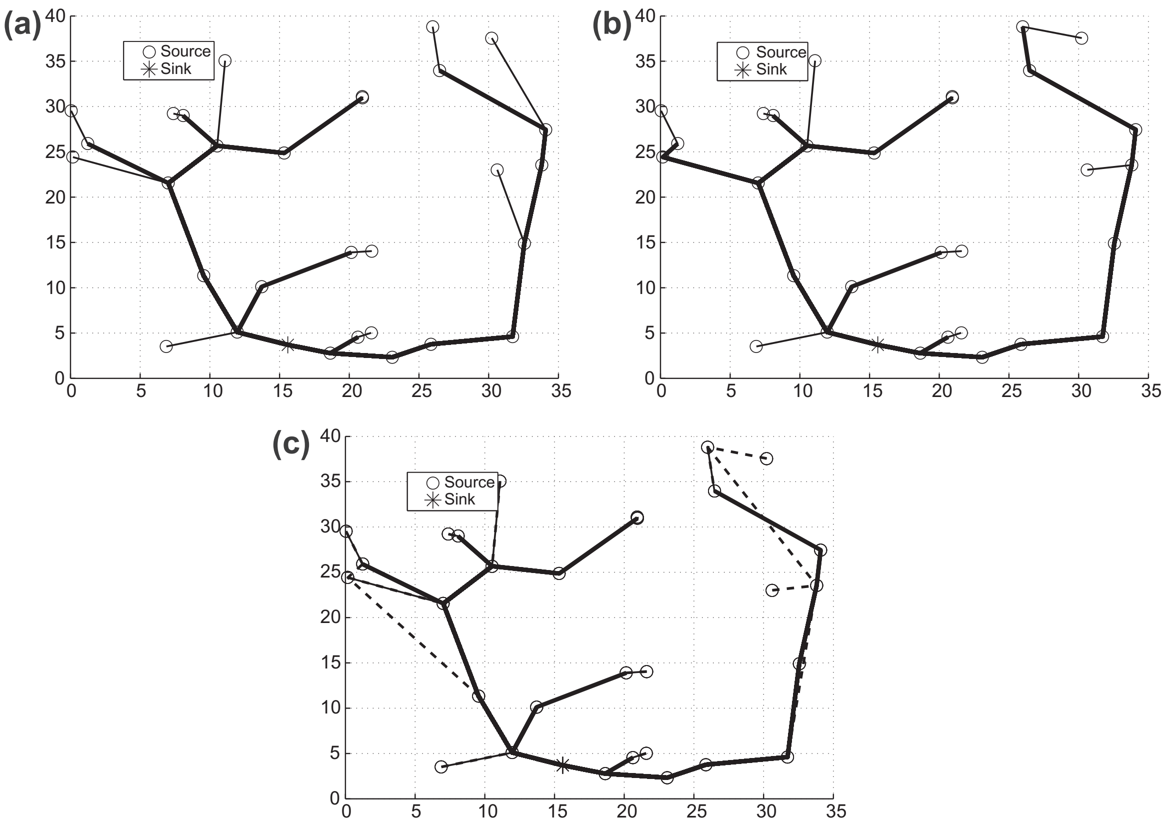

Fig. 4. Selected paths of each source and the tree structures of different routing strategies for $N = 30, c = 1000$. (a) MER. (b) CAR. (c) MEGA.

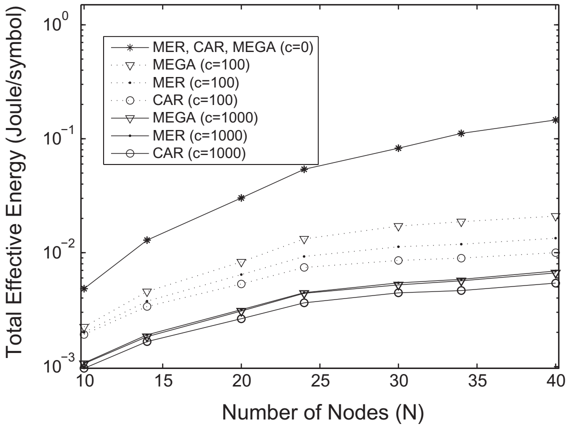

Fig. 5. Total effective energy vs. number of nodes, *N*.

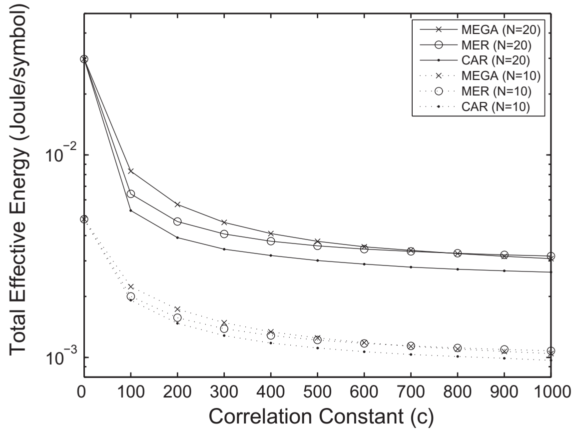

Fig. 6. Total effective energy vs. correlation constant (*c*).

corresponding utility functions, and then aggregate data opportunistically based on the routes set-up, this approach is called routing-driven aggregation [18]. Opportunistic aggregation on a given minimum energy or shortest path tree is not efficient because the data generated by nodes near the sink node cannot be further aggregated. MEGA is obtained after MER is constructed. CAR is implemented iteratively based on the best response strategy described in the previous section. Note also that, we start CAR algorithm with the same tree structure as MER respectively, hence at first iteration their total effective energy values are equal. MEGA uses foreign coding model, i.e. the aggregation is performed only at next hop, while CAR and MER performs the multi-hop aggregation model described in Section 2.1.

Through multiple iterations, the algorithms change the initial routing tree. Fig. 4 demonstrates the branches of the constructed trees for MER, MEGA and CAR algorithms under the same network topology for $N = 30$, $c = 1000$. Thick lines indicate the regions where the data aggregations are performed. For MEGA, coding tree is shown with dashed lines, whereas MER tree is shown with solid lines. The results show that different routing metrics with different utility functions lead to paths with significantly different trees or network connectivity. For example, MER tends to discover paths with lower energy while CAR searches for minimum energy routing paths to aggregate more efficiently.

5.2. Effective energy improvements

Fig. 5 shows the total effective energy per symbol in the network for CAR, MER and MEGA vs. increasing number of nodes from $N = 10$ to $N = 40$ in the network for three data correlation settings ($c = 0$, $c = 100$ and $c = 1000$). The energy improvements returned by CAR algorithm over MER and MEGA algorithms increase gradually as the network size grows. The reason is that the MER algorithm is optimized only for routing whereas MEGA and CAR algorithms are optimized for both data aggregation and routing. However, MEGA does not perform multi-hop aggregation and its performance deteriorates at large network sizes. For example

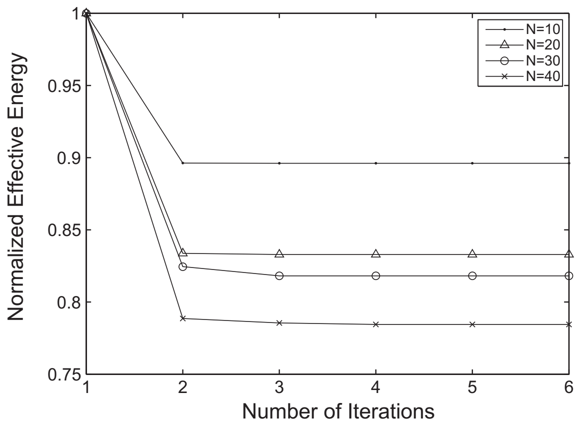

Fig. 7. Normalized effective energy consumption of CAR with respect to MER vs. number of iterations for $c = 1000$.

for $N = 10$, the percentage improvement of CAR algorithm compared to MER is 4.31 percent and compared to MEGA is 14.30 percent, whereas for $N = 40$ the improvements are around 25.35 and 52.18 percent compared to MER and MEGA respectively, at $c = 100$. Note also that MEGA's performance increases as the correlation constant increases and is almost same with MER algorithm at $c = 1000$ even though MER algorithm performs multi-hop data aggregation. The reason is that it can optimize both data aggregation and routing more efficiently at higher correlation levels.

The effective energy metric incorporates both the energy and throughput gains of the above mentioned algorithms into one performance metric. At low correlations, the effective energy improvements of the CAR algorithm over the MER algorithm are higher than the effective energy improvements at high correlations. The reason is that at high correlation levels, correlation among all nodes is so high that no matter which path is used for data aggregation and routing, the transmitted data rate can be reduced significantly. Therefore, there is not much room for further improvement by choosing a better path using the CAR algorithm after MER is established at strong correlation levels. For example, if full data aggregation is performed, i.e. when $c \to \infty$, the performance of all algorithms are expected to perform same. From Fig. 5, we also see that compared to no data aggregation case, i.e. $c = 0$, the improvements of the CAR algorithm are 93.15 percent for $c = 100$ and 96.29 percent for $c = 1000$ when $N = 40$. These results show the significant performance gain and advantage of performing in-network data aggregation of correlated data compared to no aggregation schemes in the network.

5.3. Impact of correlation coefficient

Fig. 6 shows the total effective energy of CAR, MER and MEGA algorithms as the correlation constant c increases from 0 to 1000 for different network sizes. The performances of all algorithms improve as the data correlation becomes larger for the same network size. This shows that the routing algorithm performances can greatly benefit from data aggregation by reducing redundancy among correlated data. Both MEGA and CAR algorithms benefit more from the correlation increments than the MER algorithm since both algorithms are optimized for data aggregation. For example, for correlation parameter of $c = 200$, the percentage energy improvements of CAR over MER and MEGA are on the order of 16.73 and 31.46 for network size of $N = 20$ respectively, whereas, for correlation parameter of $c = 800$, the percentage improvements are 16.36 and 16.61 respectively. Moreover, the percentage improvements of CAR at $c = 1000$ are 16.70 and 10.40 compared to $c = 0$ (no aggregation) case when $N = 20$ and $N = 10$ respectively. MER and CAR algorithms achieve less energy consumptions for the smaller network size ($N = 10$) than larger network size ($N = 20$) under all correlation situations. In this case, both the additional number of transmissions and the interference in the network increase with increasing number of nodes which is observed from Fig. 5.

5.4. Convergence of the algorithm

In addition to the effectiveness of CAR, the number of iterations for the convergence of the proposed distributed algorithm is also important. In this section, we show the minimum number of required iterations for the convergence of the CAR algorithm for different network sizes. Fig. 7 shows the normalized effective energy consumptions of CAR compared to MER vs. number of iterations. The minimum number of iterations κ required for the total effective energy to converge is 3–4 iterations for the network size ranging from 10 to 40 nodes. We note also, that the most significant performance improvements are occurring in the first two iterations, subsequent iterations leading to diminishing returns.

The existence of a NE for CAR algorithm is illustrated by the convergence of the curve in Fig. 7. Furthermore, it can be seen that the proposed CAR algorithm involves a small number of iterations after MER is established, and has the advantage that it can be implemented efficiently in a distributed fashion.

6. Conclusions and future work

In this paper, we have addressed the problem of designing an efficient transmission structure in a wireless sensor network where all sensor nodes aggregate correlated data over intermediate nodes on route to the sink. We have investigated the impact of data aggregation in establishing routing paths towards the sink for the energy minimization problem. For correlation aware routing, we have proposed a distributed iterative protocol based on a game theoretic framework, which is shown to converge within a couple of iterations. An extensive set of simulations shows that unlike MEGA and MER algorithms which perform well under the foreign coding model and uncorrelated data respectively, CAR performs well under various sensor correlations and network topologies. Therefore, by accounting for the correlation structure, interference and multi-hop aggregation in constructing routes, significant effective energy gains over the classic approaches can be achieved by our proposed routing solution.

We note that although in this paper we specifically address the problem of effective energy minimization, the approach can be extended to other relevant cost metrics, such as network lifetime maximization, network throughput maximization, or end-to-end transmission delay minimization. The quantitative analysis of energy-delay tradeoff with the appropriate definition of delay is another research topic for future work.

Appendix A. Proof of Theorem 1

Suppose there exists a potential function of the congestion game Γ having the potential function defined as follows:

$$\mathcal{P}(S_i, S_{-i}) = -\sum_{f \in \mathcal{F}} w_f(\Psi_f(\theta_f(S_i, S_{-i}))), \tag{A.1}$$

where f is the facility and $\mathcal{F}$ is the set of facilities as defined in Section 3.2.1. Let $S_i \in \mathbf{S}_G$ be the strategy of source Y_i, $i = 1, \ldots, N$, i.e. the collection of nodes used for relaying and aggregating and $S_i' \in \mathbf{S}_G$ be another strategy. Then,

$$\begin{aligned}
\mathcal{P}(S_i, S_{-i}) &= -\sum_{f \in \mathbf{F}} w_f(\Psi_f(\theta_f(S_i, S_{-i}))), \\
&= \left(-\sum_{f \in S_i \setminus S^*} w_f(\Psi_f(\theta_f(S_i, S_{-i}))) \right) \\
&\quad + \left(-\sum_{f \in S_i' \setminus S^*} w_f\left(\Psi_f\left(\theta_f^{-i}(S_i, S_{-i})\right)\right) \right. \\
&\quad \left. -\sum_{f \in S^*} w_f(\Psi_f(\theta_f(S_i, S_{-i}))) \right) \\
&\quad + \left(-\sum_{f \in \mathcal{F} \setminus \{S_i \bigcup S_i'\}} w_f\left(\Psi_f\left(\theta_f^{-i}(S_i, S_{-i})\right)\right) \right),
\end{aligned} \tag{A.2}$$

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

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$$Q\left(S_{-i,-i'}\right) = -\sum_{f\in\mathcal{F}\setminus\left\{S_i\bigcup S_i'\right\}} w_f\left(\Psi_f\left(\theta_f^{-i}(S_i,S_{-i})\right)\right). \tag{A.3}$$

Then,

$$\mathcal{P}(S_i,S_{-i}) = \left(-\sum_{f\in S_i\setminus S^*} w_f(\Psi_f(\theta_f(S_i,S_{-i})))\right) + \left(-\sum_{f\in S_i'\setminus S^*} w_f\left(\Psi_f\left(\theta_f^{-i}(S_i,S_{-i})\right)\right) - \sum_{f\in S^*} w_f(\Psi_f(\theta_f(S_i,S_{-i})))\right) + Q\left(S_{-i,-i'}\right). \tag{A.4}$$

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

$$\mathcal{P}(S_i',S_{-i}) = \left(-\sum_{f\in S_i\setminus S^*} w_f\left(\Psi_f\left(\theta_f^{-i}(S_i',S_{-i})\right)\right)\right) + \left(-\sum_{f\in S_i'\setminus S^*} w_f(\Psi_f(\theta_f(S_i',S_{-i}))) - \sum_{f\in S^*} w_f(\Psi_f(\theta_f(S_i',S_{-i})))\right) + Q\left(S_{-i,-i'}\right). \tag{A.5}$$

Neither $Q\left(S_{-i,-i'}\right)$ nor $-\sum_{f\in S^*} w_f\left(\Psi_f\left(\theta_f(S_i',S_{-i})\right)\right)$ are affected when source Y_i changes its strategy. Therefore,

$$\mathcal{P}(S_i',S_{-i}) - \mathcal{P}(S_i,S_{-i}) = \left(-\sum_{f\in S_i\setminus S_i^*} w_f\left(\Psi_f\left(\theta_f^{-i}(S_i',S_{-i})\right)\right) - \sum_{f\in S_i'\setminus S^*} w_f\left(\Psi_f\left(\theta_f(S_i',S_{-i})\right)\right)\right) - \left(-\sum_{f\in S_i\setminus S^*} w_f(\Psi_f(\theta_f(S_i,S_{-i}))) - \sum_{f\in S_i'\setminus S^*} w_f\left(\Psi_f\left(\theta_f^{-i}(S_i,S_{-i})\right)\right)\right). \tag{A.6}$$

From (11) and the definition for $w_f(.)$ in (10),

$$\begin{aligned}
&u_i(S_i',S_{-i}) - u_i(S_i,S_{-i}) \\
&= \left(-\sum_{f\in S_i'} \left(w_f(\Psi_f(\theta_f(S_i',S_{-i}))) - w_f\left(\Psi_f\left(\theta_f^{-i}(S_i',S_{-i})\right)\right)\right)\right) \\
&\quad - \left(-\sum_{f\in S_i} \left(w_f(\Psi_f(\theta_f(S_i,S_{-i}))) - w_f\left(\Psi_f\left(\theta_f^{-i}(S_i,S_{-i})\right)\right)\right)\right), \\
&= \left(-\sum_{f\in S_i'\setminus S^*} \left(w_f(\Psi_f(\theta_f(S_i',S_{-i}))) - w_f\left(\Psi_f\left(\theta_f^{-i}(S_i',S_{-i})\right)\right)\right)\right) \\
&\quad - \left(-\sum_{f\in S_i\setminus S^*} \left(w_f(\Psi_f(\theta_f(S_i,S_{-i}))) - w_f\left(\Psi_f\left(\theta_f^{-i}(S_i,S_{-i})\right)\right)\right)\right), \\
&= \left(-\sum_{f\in S_i\setminus S^*} w_f\left(\Psi_f\left(\theta_f^{-i}(S_i,S_{-i})\right)\right) - \sum_{f\in S_i'\setminus S^*} w_f(\Psi_f(\theta_f(S_i',S_{-i})))\right) \\
&\quad - \left(-\sum_{f\in S_i\setminus S^*} w_f(\Psi_f(\theta_f(S_i,S_{-i}))) - \sum_{f\in S_i'\setminus S_i} w_f\left(\Psi_f\left(\theta_f^{-i}(S_i',S_{-i})\right)\right)\right).
\end{aligned}$$

Note that

$$-\sum_{f\in S_i\setminus S^*} w_f\left(\Psi_f\left(\theta_f^{-i}(S_i,S_{-i})\right)\right) = -\sum_{f\in S_i\setminus S^*} w_f\left(\Psi_f\left(\theta_f^{-i}(S_i',S_{-i})\right)\right),$$

and

$$-\sum_{f\in S_i'\setminus S_i} w_f\left(\Psi_f\left(\theta_f^{-i}(S_i',S_{-i})\right)\right) = -\sum_{f\in S_i'\setminus S_i} w_f\left(\Psi_f\left(\theta_f^{-i}(S_i,S_{-i})\right)\right).$$

Hence,

$$u_i(S_i',S_{-i}) - u_i(S_i,S_{-i}) = \mathcal{P}(S_i',S_{-i}) - \mathcal{P}(S_i,S_{-i}). \tag{A.7}$$

Then, $\mathcal{P}(S_i,S_{-i})$ defined in (13) is an EPG of game Γ.

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