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An Investigation of Protocols for wireless networks that allow for effective data communication

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Abstract: Wireless sensor networks, also known as WSNs, are one of the technologies that are now seeing the most rapid growth. This is due to the fact that WSNs have a wide variety of applications and an impressively capable set of features. However, because of the low energy capacity of the sensor nodes that make up WSNs, the longevity of these networks is severely constrained. Because of this, preserving energy is regarded as the most essential research problem for wireless sensor networks (WSNs). Within a WSN, the function that uses the most energy is the one that deals with radio transmission. Therefore, in order to conserve energy and therefore extend the lifespan of WSNs, energy-efficient routing is required to be implemented. As a result of this, a great number of protocols for the implementation of energy-efficient routing in WSNs have been suggested.

Index Terms **- WSNs, System Model, Framework energy-efficient routing, Simulation**

1.1 Introduction

The data collected by various nodes within an area by wireless sensor networks (WSNs) are strongly associated with one another. For instance, if the data consist of random variables, such as temperature readings, then the values that are obtained at each node will be geographically and temporally linked with one another. It is possible for the destination nodes to experience a rise in traffic and data redundancy if all sensor data is sent. This might lead to a significant increase in the network's total use of energy. WSNs may realise the benefits of multi-hop routing via the use of data aggregation all along the path that extends from the most remote sensor node to the network sink. Routing in multi-hop WSNs requires energy awareness and correlation knowledge. When many types of data are aggregated into one, the routing choices may be significantly altered [1].

The majority of routing algorithms used in WSNs have the overarching goal of reducing the overall transmission cost incurred by moving the data acquired by nodes in a way that is spread. WSN routing approaches focus different metrics based on application and design characteristics. WSNs survive longer with energy-efficient routing. MER is energy-efficient routing. In order to reduce the amount of energy consumed for transmission, the MER algorithm has been implemented [2, 3].

The goal of routing with data aggregation is to determine the best network architecture for collecting the most highly correlated data while simultaneously lowering the cost function in sensor networks with limited resources. It is not surprising that knowledge of correlations has a major impact on routing algorithms, which is why this topic deserves further study in multi-hop WSNs. Data aggregation at each node in the multi-hop trip has been the subject of recent studies [4] that explore the prospect of capitalising on the correlation between the data.

An information theoretic approach to investigate the relationship between routing and data aggregation. Each node's routing choices are influenced by both transmission and aggregation costs [5]. The self-coding model is used to prove that the general cost-minimizing optimisation issue is NP-complete. Between the SPT and the travelling salesman route, this is the best answer we can come up with. Because it is difficult to identify the optimum routing solution (NP-hard), the authors evaluate numerous heuristic approximation techniques in order to create correlated data collecting trees and then compare their performance to a benchmark that is based on simulated annealing. The ideal MEGA for aggregating data from external coding, whereas the LEGA approximation is used for self-coding. These models only allow for a limited amount of data aggregation to take place. It is difficult to re-encode the data after it has been aggregated since the data can no longer be modified in the packet at any subsequent node along the way. Both the coding tree (a minimal spanning tree that is directed for the raw data.) and the SPT (which saves aggregated data) are kept in MEGA, which is based on the foreign coding paradigm. LEGA, a shallow light tree-based self-coding model, approximates $2(1 + \sqrt{2})$. MEGA and LEGA perform badly in dense networks or strong correlation despite approximation algorithms that are optimum or close to optimal for their data models. This is because there is no practical way to take advantage of the fact that all nodes share redundant data. It is impossible to reduce duplication between source nodes since each node can only aggregate once.

Researchers study WSN tree construction technologies including routing-driven aggregation and static cluster-based routing. For the purpose of opportunistic data aggregation over SPT, we demonstrate static cluster-based routing in addition to route-driven aggregation. The authors of investigate the effects of several network hops on data aggregation, foreign coding, and self-coding. Data may be aggregated (or compressed) at several hops using the suggested models, allowing for even further reduction.

This work proposes a multi-hop data aggregation methodology that uses source data correlation across neighbour nodes to gather correlated data energy-efficiently. Energy metric, interference, and multi-hop data aggregation make it unique. The routing method considers node correlations to save electricity. To address the issue of data correlation, a simple game-theoretic model is constructed, complete with utility functions. We employ numerical simulations to compare the effectiveness of various routing algorithms and to highlight the possible benefits of our suggested techniques.

1.2 System Model

We specialise in WSN data collection and routing. Sensor nodes collect pictures or environmental data in surveillance cameras and other image-based monitoring and tracing systems. Data routing decreases redundancy. Thus, we study maximum correlated data collection utilising one sink to convey all data. All source nodes gather, transmit, and aggregate data. N source nodes, V is the set of all nodes, including source nodes and one sink node, and E is the set of edges, or potential linkages between nodes. If two nodes can communicate, they have an edge. Set A has |A| elements. |V| = N + 1, and |E| ≤N (N + 1)/2. Network graph G = (V, E). R ⊂ V where |R| = N is the collection of source nodesY_1–Y_N sources. We assume all node data flows via D for simplicity. This method may transport data from distinct node subsets to multiple sinks. Nodes are randomly distributed. Network energy-minimizing algorithm. Effective connection communication requires a goal bit error rate (BER). Our system cannot fix mistakes. Erroneous packets are automatically retransmitted M packets. Then the probability of packet receipt is $Pc(\gamma) = (1 - 2BER(\gamma))M$ where $BER(\gamma)$ is the bit error rate corresponding to a (SINR) γ. Modulation technique and noise and interference environment affect BER (γ). This study assumes a Gaussian cumulative interference CDMA system. Under Gaussian noise and interference, non-coherent frequency shift keying modulation has $BER(\gamma) = 0.5 \exp(-0.5\ \gamma)$. This equation determines the system's goal SINR γ^*.

DS-CDMA with varied spreading sequences is used in our system. Each transmitter's spreading factor, L, may be changed to satisfy QoS (or SINR) targets. To attain a target SINR, Yi and Yj must spread SINR, γ∗, is [6].

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

link gain $h_{i,j} = {}_{i,j}$, $dp_{i,j}$, where di,j is the distance between nodes Y_i and Y_j, p is referred to as the route loss exponent, and it has a value that is typically in the range of 2 to 4 for radio transmissions that take place in open space and short-to-medium distances. Thermal noise σ^2 power, $L_{i,j}$: $\Omega_{i,j} = W/L_{i,j}$ where W is the system bandwidth.

Joules per bit is the unit of measurement for the energy required to transmit one bit of data in a packet. This study exclusively covers transmission energy, ignoring reception and data processing. For packet communications between nodes Y_i and Y_j, energy per bit i,j b is defined as

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

where M is packet length, m is information delivered, and P_i is transmit power. Y_i, i = {1, 2, ..., N }.

Sources' data rates or weights are used to quantify each sensor node's data output and data aggregation along the path. Sensor node data is believed to be geographically connected. Thus, depending on the field density of WSNs, neighboring nodes' readings may be strongly linked and include data redundancies. The data rate of each source node Y_i is. Data rate Ψ (Y_i) is symbol encoding rate, not data transmission rate. Data rate Ψ (Y_i) represents the data source's average bits/symbol. Source nodes, depicted by circles in Fig. 1.1, may send their raw data to the sink or aggregate data from other source nodes. The node sends the sink aggregated data. Save network energy.

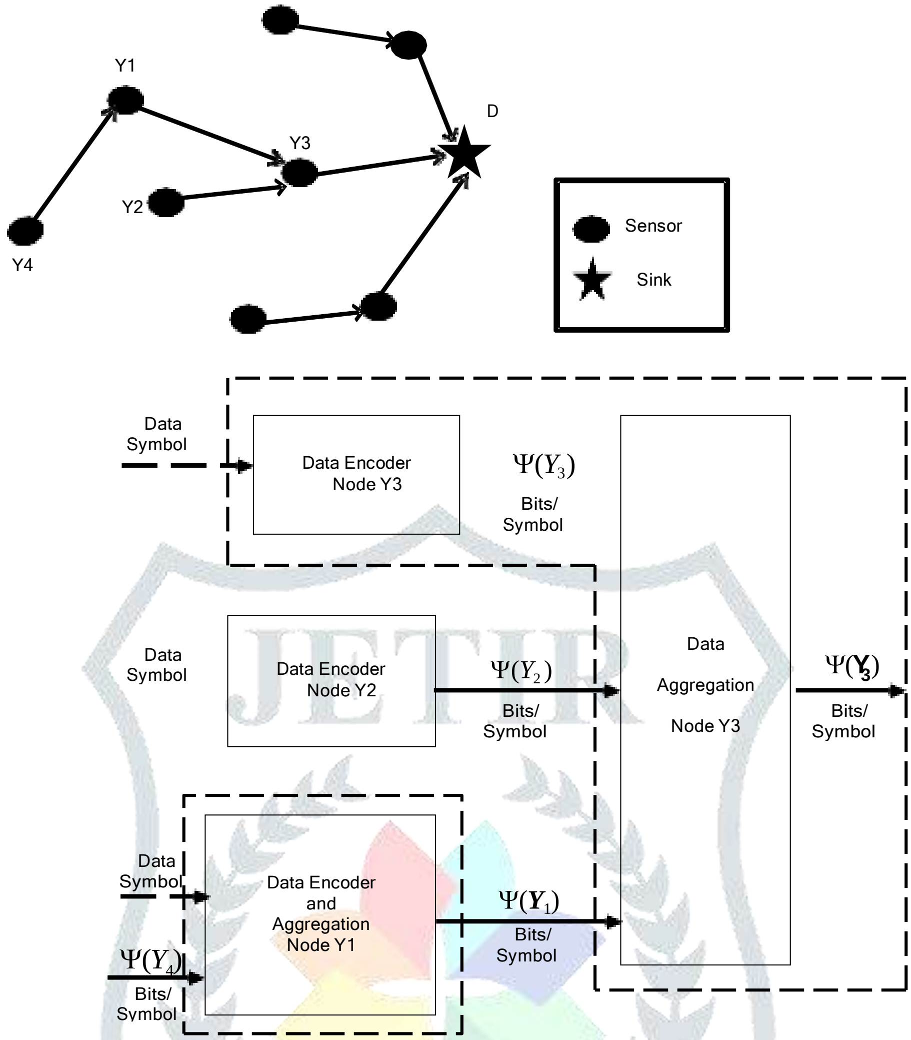

Figure 1.1: Data collecting tree. Intermediate source nodes aggregate encoder data to reach sink D

1.3 Framework for effective energy-efficient routing

The data rate of a node's sources and its transmission energy determine its symbol transmission energy. For data redundancy through correlation, the energy needed per symbol during transmission between nodes Y_i and Y_j may be represented as

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

where $\Psi_i(Y_i)$ is the pace of data collection overall at node Y_i and Y_i is the set of all q sources using node Y_i including Y_i, i.e. $Y_i = \{Y_i, Y_1, Y_2, \ldots, Yq\}$. Units exist for the necessary energy per symbol. The energy required to send one data symbol without a glitch is measured in terms of joules per symbol, or joule/symbol. It's possible for the throughput symbol of a connection to be thought of as the equivalent of energy per symbol between nodes Y_i and Y_j is defined as

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

Symbol throughput is the number of symbols sent per second. Routing issues impact symbol throughput of source-created data ζi. Y_i is the lowest symbol throughput link from source Yi to data sink D, defining each source's symbol throughput. This connection bottlenecks that source node. Nodes linked to sink through same node have the lowest bottleneck throughput. The network and physical energy minimization challenge is:

$$\underset{S_i \in X_i}{\text{Minimize}} \sum_{i=1}^{N} \sum_{k,l \in S_i} E_s^{k,l}(\Psi_k(\mathbf{Y}_k)),$$

$$\text{subject to } \text{SINR}_{k,l} \geq \gamma^*, \ \ P_k = C,$$

$\text{SINR}_{k,l}$ is the signal-to-interference-and-noise ratio that was measured at node Y_l for the connection that connects nodes Y_k and Y_l. $P_k = C$ is the constant transmit power that node Y_k was using. Y_k, i.e. $Y_k = \{Y_k, Y_1, Y_2, \ldots, Yq\}$, S_i is the a collection of nodes that are utilised for source relaying and aggregation Y_i, and X_i is the set of all of the potential relaying and aggregating nodes along a path leading from a sourceY_i.

Each node employs multi-hop aggregation when all sensors follow the data aggregation strategy outlined in Section, making it difficult to discover the best routing method. Even with the simpler self-coding data aggregation methodology, [7] it is proven that the combined optimisation of transmission cost and data aggregation is NP-complete. Consequently, determining the best strategies for minimising energy use is an NP-hard optimisation issue. Therefore, we present a distributed energy reduction technique that makes use of the network's correlation structure. A game-theoretic formulation is proposed, and it is proven to converge to a local optimum solution in a distributed manner with minimal complexity.

1.4 In the context of the congestion game, facility cost selection

The issue of creating the data-gathering tree with the lowest possible energy expenditure due to correlations is considered. The following factors may be taken into account when establishing facility costs:

- The amount of energy that was used to convey bits or symbols on outbound lines from the facility;

- The possibility of aggregation.

1.5 Simulation Results

Using a combination of logical reasoning and computation, we may infer that our CAR method is superior than the competition. The Section aggregation model gathers MER and CAR algorithm data at various sink nodes. Different methods compare network size, correlation coefficient, and convergence iterations for randomly distributed 2D nodes. Based on design parameter, we compare our CAR algorithm's energy savings to MER and MEGA._All algorithms are compared on the basis of their overall network energy consumption per symbol, with the total symbol throughput ζtotal = ΣN, i=1 λi requirement. When the total number of symbols generated in a given length of time is equal for all algorithms, then the effective energy per symbol is compared. Effective energy improvements include the energy and throughput advantages in a single performance indicator.

Step-

In this experiment, we equally place N sensor nodes in a 40m x 40m square, with N ranging from 10 to 40. We use the ubiquitous Gaussian random field data correlation model [8]. According to this model, the distance between pairs of nodes Y_i and Y_j decreases the correlation coefficient $\rho_{i;j}$ between them exponentially: $d_{i;j}$, i.e. $\rho_{i;j} = \exp(-d_{2\ i;j}/c)$, where c is the correlation constant: $0m^2$ for no aggregation, $100m^2$ for low correlation, $1000m^2$ for strong correlation. Path loss P=2. Our simulations use a "forgetting" factor of 0.8 per link to decrease the correlation i;j between information gathered at node Y_i and its routing tree parent node Y_j. Thermal noise power is W = 1 Mhz is $\sigma^2 = 10^{-13}$ Watts. All nodes transmit $P_i = 10^{-2}$ Watts, $\forall i \in N$. Each packet has 80 data bits and no overhead (m = M = 80). SINR is $\gamma^* = 5$ (7 dB), For every $Y_i \in N$, each source's raw data rate is assumed to be constant, and each symbol is represented with Ψ(Yi) = 1 bits/symbol of information.

We compare the approaches' overall effective energy usage at ζ total = 100 kbps symbol throughput.

The outcomes for each routing method are an average of simulations of one hundred unique network configurations. Dijkstra's algorithm speeds up the MER method's sink-source route determination. We design pathways using utility functions and grab data opportunistically. MEGA follows MER, therefore convergence takes two rounds. CAR iteratively applies the best response strategy. The overall effective energy values at the first iteration of the CAR and MER algorithms are identical since CAR starts with MER's tree structure. MEGA uses a foreign coding paradigm to aggregate at the next hop, unlike CAR and MER.

The techniques iteratively modify the basic route tree. Trees were built for the MER, MEGA, and CAR algorithms with the identical network architecture and parameters (N = 30, c = 1000). Data aggregations are conducted in the places where the lines are thickest. In contrast to the solid lines used to depict the MER tree, MEGA's coding tree uses dashed lines. The findings demonstrate that routes with drastically different trees or network connections arise from using routing metrics with distinct utility functions. For instance, MER favours finding low-energy pathways whereas CAR prioritises finding the least-energy-intensive aggregated path possible.

1.6 Conclusion

In this paper, we addressed the challenge of developing an effective transmission topology for wireless sensor networks, in which data from several sources is sent via a series of intermediary nodes before arriving at the washbasin. We have explored how the construction of routing pathways towards the sink is affected by the effective aggregation of data as a means of overcoming the challenge associated with doing so. We have proposed a game-theoretic framework for an iterative, distributed protocol for correlation-aware routing. The protocol is based on correlation-aware routing. It has been shown that after a few iterations of the procedure, the protocol will converge on the desired result. In addition, we have shown that significant effective energy gains may be gained when, while creating routes, multi-hop aggregation and correlation structure are taken into consideration. This is in comparison to traditional methods.

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