World Academy of Science, Engineering and Technology
International Journal of Computer and Information Engineering
Vol:3, No:7, 2009

Effect of Clustering on Energy Efficiency and Network Lifetime in Wireless Sensor Networks

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Abstract—Wireless Sensor Network is Multi hop Self-configuring Wireless Network consisting of sensor nodes. The deployment of wireless sensor networks in many application areas, e.g., aggregation services, requires self-organization of the network nodes into clusters. Efficient way to enhance the lifetime of the system is to partition the network into distinct clusters with a high energy node as cluster head. The different methods of node clustering techniques have appeared in the literature, and roughly fall into two families; those based on the construction of a dominating set and those which are based solely on energy considerations. Energy optimized cluster formation for a set of randomly scattered wireless sensors is presented. Sensors within a cluster are expected to be communicating with cluster head only. The energy constraint and limited computing resources of the sensor nodes present the major challenges in gathering the data. In this paper we propose a framework to study how partially correlated data affect the performance of clustering algorithms. The total energy consumption and network lifetime can be analyzed by combining random geometry techniques and rate distortion theory. We also present the relation between compression distortion and data correlation.

Keywords—Clusters, multi hop, random geometry, rate distortion.

I. Introduction

Wireless Sensor networks is among the fastest growing technologies that have a potential of changing our lives drastically. These collaborative, dynamic and distributed computing and communicating system will be self organizing. A Wireless Sensor Network (WSN) is multi hop self configuring wireless network. It consist of many small, light weight sensor nodes (SNs) called *motes*, deployed on the fly in large numbers to monitor the environment or a system by the measurement of physical parameters such as temperature, pressure or relative humidity. A sensor network is designed to perform a set of high-level information processing tasks such as detection, tracking, or classification. Measures of performance for these tasks are well defined, including detection of false alarms or misses, classification errors, and track quality.

Applications of sensor networks are wide ranging and can vary significantly in application requirements, modes of deployment (e.g., ad hoc versus instrumented environment), sensing modality,or means of power supply (e.g., battery versus wall-socket).They will have capabilities of distributing a task among themselves for efficient computation. There are many challenges in implementation of such systems: Energy dissipation and clustering being one of them.

In order to maintain certain degree of service quality and a reasonable system lifetime energy needs to be optimized at every stage of system operation. Nodes that are clustered together will easily able to communicate with each other. Clustering is the process of grouping of nodes so that data from sensor nodes of a group can be combined or compressed together and transmit only compact data.

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Node clustering techniques fall into two categories based on construction of a dominating set and solely based on energy considerations. The first category suffers from the fact that only a small subset of the network nodes are responsible for relaying the messages, and thus cause rapid consumption of the energy of these nodes. The second category uses the residual energy of each node in order to direct its decision about whether it will elect itself as a leader of a cluster or not.

Data aggregation schemes for wireless sensor networks have been used as mechanisms to generally optimize energy consumption. The schemes are used to reduce the total amount of sensor readings by means of performing a variety of aggregate operations and collaborating with sensor nodes in data transmission. Each cluster elects a cluster-head node, and routing is done only among the cluster-heads (the remaining nodes always route packets through their cluster-heads). This is advantageous for a variety of reasons, including the possibility of using simpler communication protocols within a cluster, recycling of resources (such as frequency assignments) among disjoint clusters, and saving power.

Various clustering protocols have been proposed either in the context of generic wireless ad hoc net- works or wireless sensor networks. These protocols either do not consider data correlation or assume ideal data aggregation, where data are perfectly correlated, such that an arbitrary number of packets within a cluster can be compressed to one packet. However in practical sensor networks, the performance of data aggregation is closely related to the various levels of data correlation. This necessitates additional study into the characteristics of clustering with partially correlated data. Wireless Sensor Networks are used in military applications, monitoring, guidance systems of intelligent missiles, and direction of attacks. Sensors are also used in environmental applications such as forest fire detection, earth quake monitoring and habitat exploration of animals and useful in patient diagnosis and monitoring. Smart sensor nodes can be built into appliances at home such as ovens refrigerators and vacuum cleaners. The environment can provide a (smart home) which adapts itself according to users tastes.

Contribution: In this paper, we consider the effect of partially correlated data on the performance of clustering algorithms.

As far as we are aware, this is the first paper that provides a comprehensive analytical framework to evaluate the energy and lifetime performance of clustering in sensor networks. The proposed analysis is generic and can be applied to a wide array of random clustering algorithms.

Organization: The rest of this paper is organized as follows. Section II presents the related work; in Section III define the system model used in our analysis. Sections IV, V, and VI, we present network lifetime, network energy consumption and numerical analysis on data forwarding, sensor data correlation, network energy consumption, and network lifetime respectively.

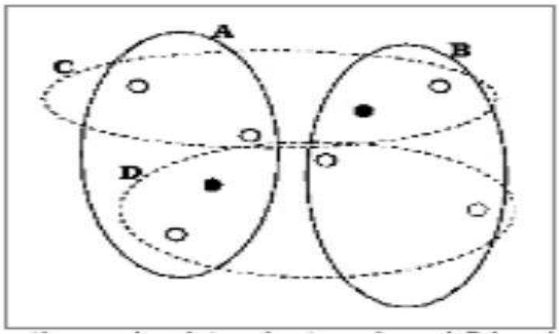

Fig. 1. Partitioning the nodes into clusters A and B leads to a solution dissipating less communication energy compared to clusters C and D.

II. RELATED WORK

Many clustering algorithms and protocols have been proposed in the past to improve the scalability of multi-hop wireless networks. They include single-hop clustering, first introduced in [1] multi-hop clustering, for example [2]. Most of these algorithms do not consider energy consumption or network lifetime. With few exceptions, energy-aware clustering algorithms have been proposed mostly in the context of wireless sensor networking. They include [3] and [4]. Particularly, in [3] and [4], it has been noted that there exists an optimal number of clusters that minimizes total energy consumption.

In [5], the optimal number of databases, which correspond to cluster of the cluster head probability to balance this trade-off based heads, and their optimal arrangements have been derived for on application demands and hardware characteristics, as well location and resource management. However, none of these as the cost of sensor battery replacement algorithms consider the performance of data aggregation based on various data correlation levels.

Various distributed signal estimation protocols have been proposed for sensor networks. In [6], a distributed estimation algorithm is proposed for a subclass of periodic aggregation problems in which the result of aggregation is determined by the values of a few nodes. In [7], a distributed and adaptive signal processing algorithm is used to reduce the energy consumption. In [8], data funneling is proposed, in which border nodes of a queried region do the data aggregation and forward data to the sink. None of these works studies clustering or its effect on signal estimation.

In [9], the lifetime of a heterogeneous single-hop clustered network is analyzed, where the cluster-heads are high-capacity nodes that communicate directly with the data sink. In our work, we consider a flat network architecture, where all nodes have the same transmission power and communicate through multi-hop routing. All clustering protocols discussed so far either do not consider data correlation or assume ideal aggregation, where an arbitrary number of packets within a cluster can be compressed into one packet. The ideal aggregation assumption is not valid in most applications. Except for the case of averaging or taking extrema, typically we need to observe data samples over an entire measured signal field. In this case, the objective is to provide a reasonable estimate of the signal field at any arbitrary point in the network.

In this work, we provide a novel framework to analyze the energy and lifetime performance of clustering algorithms,with a realistic routing protocol, under general data correlation functions and arbitrary compression distortion constraints. To the best our knowledge no previous work has presented similar mathematical analysis on the effects of non-ideal aggregation on clustering in multi-hop sensor networks.

III. SYSTEM DESIGN

A. Sensor deployment and features

A wireless sensor network consists of a set of sensors and one processing center or data sink. The denotion of the density in the underlying Poisson point process is γ. The number of sensors located in a region R, N(R), follows a Poisson distribution of parameter $\gamma|R|$, where $|R|$ represents the area of the region. We assume that all sensors in the network as well as the processing center are stationary. Sensors are aimed to be extremely small, inexpensive, and simple devices. Therefore, all sensors within the network are assumed to transmit at a fixed transmission power, and each sensor has the same radio range R. All sensors are equipped with a battery that has an initial amount of energy equal to E_0 . We assume that each sensor requires 0.5 units of energy to transmit or receive one unit of data. We assume that the communication environment is contention and error-free, and therefore sensors do not have to retransmit any data.

Cluster formation, is one of important concern in sensor network applications and can drastically affect the network's communication energy dissipation. Clustering is performed by assigning each sensor node to a specific master node. All communication to (from) each sensor node is carried out through its corresponding master node. Obviously one would like to have each sensor to communicate with the closest master node to conserve its energy, however master nodes can usually handle a specific number of communication channels. Therefore there is a maximum number of sensors that each master node can handle. This does not allow each sensor to communicate to its closest master node, as that master node might have already reached its service capacity.

B. Clustering protocols

Sensors in these multi-hop networks detect events and then communicate the collected information to a central location where parameters characterizing these events are estimated. The cost of transmitting a bit is higher than a computation [10] and hence it may be advantageous to organize the sensors into clusters. In the clustered environment, the data gathered by the sensors is communicated to the data processing center through a hierarchy of cluster heads. The processing center determines the final estimates of the parameters in question using the information communicated by the cluster heads. The data processing center can be a specialized device or just one of these sensors itself. Since the sensors are now communicating data over smaller distances in the clustered environment, the energy spent in the network will be much lower than the energy spent when every sensor communicates directly to the information processing center. Many clustering algorithms in various contexts have been proposed. Most of these algorithms have a time complexity of $O(n)$, where n is the total number of nodes. Many of them also demand time synchronization among the nodes, which makes them suitable only for networks with a small number of sensors.

To forward data to cluster head, and from cluster head to the processing center, we assume that nodes use light weight Minimum Hop Routing (MHR). The advantage of MHR is two fold. First, it matches well with the fixed transmission power of inexpensive sensors. Second, since the sensors are stationary, MHR requires very infrequent route updating and hence much less energy consumption than other more active routing protocols such as energy-based routing. We assume a generic clustering algorithm where CHs are selected randomly. One example of implementing a random clustering algorithm is presented in [**?**] in which CHs are selected uniformly throughout the network. The clustering algorithm is run every T units of time, where T generally depends on the type of application and initial energy supply. Each T units of time is divided into M rounds, in each of which, a CH schedules nodes within its cluster and receives observed data from them. In the beginning of each T rounds, every node selects itself as a CH with a fixed probability of p . It can be easily shown from a poisson point process with density $\gamma_1 = p\gamma$.

After the CHs have been selected, each CH sends a beacon that is flooded up to k_h hops to advertise its status as a CH. Energy node that is not a CH will join the cluster whose CH is the nearest. With the specified value of k_h ,the probability that the radius of the minimum ball centered at the nucleus of clusters CHs is bigger than kh hops, is less than α. We typically set $\alpha = 0.001$ to ensure that most nodes can receive the beacon packet from their corresponding nearest CH within kh hops. However, it is possible that a node doesn?t receive a beacon from nearby CHs. In this case, it will select itself as a forced CH [**?**]. It is easy to see that cluster formation process has a time complexity of $O(k_h)$. After cluster formation, all CHs will schedule their sensors to begin communication. Clustering,specifically in sensor networks, could be used to solve a verity of problems. Clusters are used to transmit processed data to base stations, hence minimizing the number of nodes that take part in long distance communication (This directly affects the overall system energy dissipation). Apart from sensor networks, clustering has been applied tremendously in fields like VLSI-CAD and data mining. A classical analytic VLSI placer uses clustering for efficient standard cell placement.

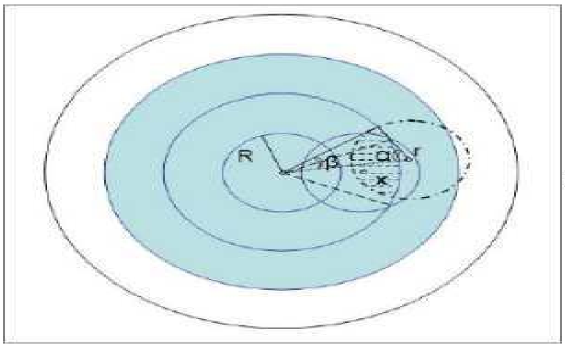

Fig. 2. Sensor network divided into layers.

Energy consumption: For our analysis we use the following definitions.

1) The sensing field is assumed to be a circular disc with radius of KR, for some integer K.
2) Nodes are distributed with density. .
3) We define Ec (r) as the conditional expected value of energy consumption of a node as a function of its distance to the processing center, i.e., if a given node is at radial distance r from the processing center, then Ec (r) is the expected value of energy consumption of that node.
4) Similarly, we define Nc (r) as the expected number of packets that a node at radial distance r from the processing .

Associated with any given point we draw a circle x showing its transmission range. In the example of Fig2 x in the second layer. Only those points which are in the intersection of the transmission range of x and the third layer can be potential nodes that will select x as their next hop. Denote one such point r . To find the probability that this occurs (i.e., when r selects x as the next hop),select point y as a point which is in the transmission range of r and is in the second layer. If points x and y are in the same layer, then from the point of view of point r, there is not considerable distinction between points x and y . As a special case, if only points x and y are present in the transmission range of r then point r will choose one of these points with equal probability. To generalize this idea, let r be a point in the k layer and within the transmission range

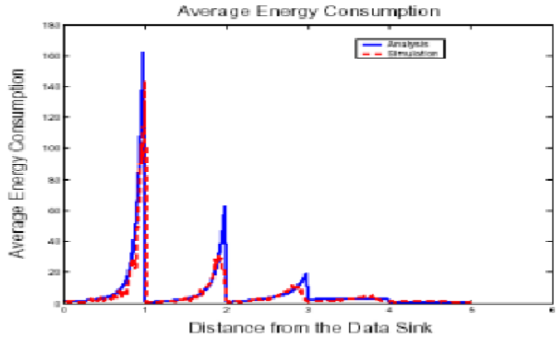

Fig. 3. Energy consumption of nodes as a function of distance.

of r, and let A(x ,r) be the intersection of circle centered at r with a radius R and the circle centered at the processing center with radius (k - 1)R. Therefore A(x,r), which is denoted by the dash-shaded region in Fig 2, shows the potential region for the next hop of point r.

To confirm the above analysis results, we have simulated 100 a network with a diameter of 5R and node density $(100\pi R_2)$. We run the simulation for 200 different networks with randomly distributed nodes and take their average. Fig 3 shows that the analysis matches the results obtained via simulation.

IV. TOTAL ENERGY CONSUMPTION

To study the total energy consumption we need to know 1) the average amount of total energy needed to communicate with the CHs and 2) the average amount of total energy that the CHs need to communicate with the data sink. As a first approximation to the routing performance, we need to know the average value of (r/R) as the average number of hops to the CHs or the average number of hops from the CHs to the processing center. Let C_0 represent a typical Voronoi cell whose nucleus is located at the origin, π_0 represent the Poisson point process associated with the non-CH nodes, and x_i be a member of π_0 , we can define a function $f(x_i)$ as a property of x_i, e.g., its distance to the CH, and S_f as the summation of that property over all cluster-members. We denote by C_1 the total energy needed to communicate with the CHs. We compute the expected value of C_1 by conditioning it by the number of clusters in the network which leads to

$$E(C_1) = E[E(C_1|n = n_0)]$$

We denote by C_2 the amount of total energy consumed by the CHs to communicate with the data sink.

$$E(C_2) = E(n_c)E(f_i/R)E(R_D(c_i))$$

The average total energy consumption is

$$E(C_t) = E(C_1) + E(C_2)$$

V. NETWORK LIFETIME

To study the behavior of network lifetime as the time that the first node dies we use the results obtained in Section III. Although there are other definitions of lifetime, we believe that for the given network model our definition is a reasonable indicator of network lifetime. Given that traffic is uniformly distributed in the network (over the long run), nodes that have the same radial distance from the processing center will deplete their energy supply approximately at the same time. From Section III, it is clear that the nodes within the first layer will run out of energy first. Furthermore, the portion of nodes that are in the first layer is small . Clearly if there is no node in the first layer then the network will fail and cannot deliver information to the data sink anymore. Therefore, the lifetime of the first node to die in the first layer is closely related to the network lifetime.

Every node has two components of energy consumption which contribute to the total energy consumption, e_t, of that node. The first part, e_{in} , is the average energy consumption due to being in a cluster either as a CH or cluster-member. This is the same for all nodes in the network, because each node is selected as a CH with the same probability (we neglect the edge effects, and clearly by CH updating, the load of being a CH is rotated periodically).

The second part, $e_{out}(r)$, is the average energy consumption due to routing data toward the data sink, which is dependent on the distance, r, from the data sink as shown previously. Clearly, ein ,is the total amount of energy consumption within a cluster divided by the total number of nodes, n_in, in a typical cluster.

$$e_in = (1-p)\sum_{k=0} R_{net} Rexp(-\gamma_1\pi(kR)$$

In the analysis previously, we have assumed that every node generates a new sensed data packet in each time unit with probability one. Clearly, if all nodes generate a packet with a probability p0, then their average energy consumption will be scaled by a factor of p0.Since the density of CH s is p and each CH has $E(R_d(c_i))$ bits to send,

$$e_{out(r)} = pE(R_D(c_i))E_c(r)$$

by combining the two previous equations we obtain

$$e_t(r) = e_{in} + e_{out}(r)$$

By definition the network lifetime is inversly proportional to the maximum of energy consumption.

$$E_{(lifetime)} \alpha min(1/e_t) = (1/e_t(1))$$

VI. NUMERICAL ANALYSIS

A. Comparison with Simulation Results

Fig. 4 shows the network lifetime as a function of p. It can be seen that our analysis accurately predicts the behavior of network lifetime. Here our analysis is compared with the simulation results of clustering with MHR. The main reason of he good match between simulation and analysis in terms of

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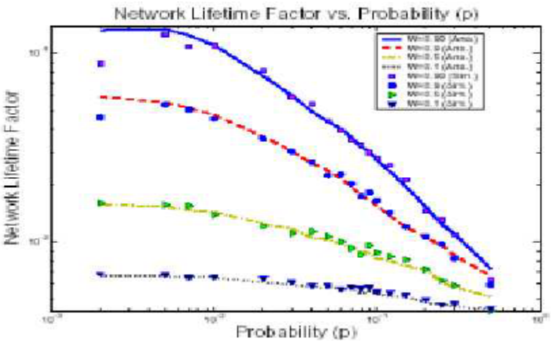

Fig. 4. Network lifetime vs. cluster head probability (Do=0.01).

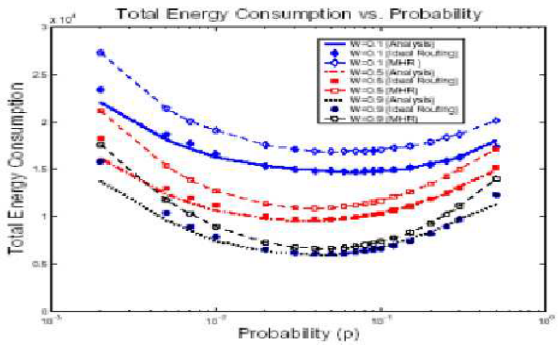

Fig. 5. Total energy consumption vs. cluster-head probability.

network lifetime is that, from the point of view of nodes in the first few layers, the number of packets that should be relayed by them determines their energy depletion rate. Therefore, inaccuracies in the path lengths do not drastically influence the energy consumption analysis of the first or the second layer nodes.

As could be expected, increasing W increases the lifetime of network by more than an order of magnitude. This has been indicated but not analyzed in the past literature. Also, increasing cluster sizes can increase the network lifetime but as Fig. 4 suggests, after a point the curves are effectively flat and there is no more gain. The discrepancy between analysis and simulation when p is small is due to the finite size of the network and inadequate experimental data when there are few clusters.

In Fig. 5 an ideal routing scheme is considered, where a node that is at distance r from a destination needs R hops to send its packets. Although this assumption may not be practical, it has been used as a guideline in the past literature especially when analyzing energy consumption [14]. As can be seen from the results, our analysis matches very well with simulation. In extreme cases where p is less than 0.005 or when it is near 0.5, the discrepancy is pronounced because of various approximations that we have made. For example, in either case, (r/R) is not an accurate estimation. Also, when the clusters are large, the finite size of our network can affect the analysis.

Fig. 5 also compares our analysis with the simulation of clustering with MHR. As can be seen, the general behavior is the same except for approximately a 15 percent scaling factor. This is because (r/R) is a lower bound to the number of hops to reach the destination and we expect longer paths for MHR as the density of nodes decreases. Despite the fact that there is a scaling factor between two curves, the optimal cluster-head probabilities match very well.

B. Trade-off between Total Energy Consumption and Network Lifetime

Fig. 6 plots the total energy consumption against network lifetime for various values of p and W . Since the analysis and simulation match well, we show only the analysis results. This figure shows that we can trade-off the total energy consumption for the network lifetime. Clearly, in applications where sensors with non-renewable batteries are used, the latter is much more important than the former. In all cases the behavior for all values of W is similar, but the optimal cluster head probability and the performance gain are functions of W .

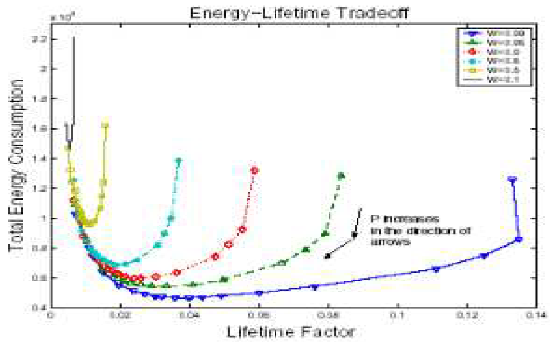

Fig. 6. Trade-off between energy consumption and lifetime.

For example, when W = 0.99, decreasing p from 0.05 to 0.005 will lead to more than 3 times the improvement in the network lifetime while it increases the total energy consumption by a factor of less than 2. In contrast W=0.5 ,the lifetime gain is less than 80 percent while the energy consumtion is increased by a factor of 70 percent.

VII. CONCLUDING REMARKS

We have proposed a distributed algorithm for organizing sensors into a hierarchy of clusters with an objective of minimizing the total energy spent in the system to communicate the information gathered by these sensors to the information-processing center. We have found the optimal efficient way to enhance the lifetime of the system is to partition the network into distinct clusters with a high energy node as cluster head. Sensors within a cluster are expected to be communicating with cluster head only. In this paper we propose a framework to study how partially correlated data affect the performance of clustering algorithms. The total energy consumption and network lifetime can be analyzed by combining random geometry techniques and rate distortion theory. We also present the relation between compression distortion and data correlation.

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