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An Environment Monitoring System Architecture Based on Sensor Networks

Ming YU, Aniket MALVANKAR, and Wei SU

Abstract— **This paper presents a an environment monitoring systems (EMS) architecture based on sensor networks, which includes a new adaptive clustering scheme and a multi-hop routing algorithm, called sensors-enabled event routing architecture (SEERA). By monitoring the received signal power from other nodes, each node estimates the number of active nodes in real-time and computes its optimal probability of becoming a cluster head (CH) in order to minimize the amount of energy consumed in both intra- and inter-cluster communications. In order to prolong the network lifetime, the multi-hop routing algorithm is designed to be both energy-efficient and power-aware, based on the clustering architecture. The new clustering and routing algorithms scale well and converge fast for large-scale dynamic sensor networks, as shown by the simulation results.**

Index Terms— **Sensor network, clustering, power-aware, energy-efficient, routing.**

I. INTRODUCTION

RAPID advances in sensor systems have enabled the development and deployment of various environment monitoring systems (EMS), in which a large numbers of small, relatively inexpensive and low-power sensors are connected via a wireless network, through which the data extracted from these sensors is sent to a nearby base station (BS), which forwards the data to a remote data center for further processing. The wireless sensor networks represent a new paradigm for EMS to monitor a variety of environments such as surveillance, machine failure diagnosis, and chemical/biological detection. A particularly challenging problem is how to dynamically organize these sensors into a wireless communication network and route detected event information between field sensors and BS, i.e., the design of a networking protocol.

The requirements for such a networking protocol can be divided into two categories: the primary requirements, including energy efficiency, scalability, adaptivity, and security; and the secondary requirements, including channel efficiency and network performance, which includes packet delay, packet loss ratio, throughput, and fairness [1]. The focuses of this paper are energy efficiency, scalability, and adaptivity. In order to prolong the network lifetime, the networking protocol should be energy-efficient as well as power-aware. By energy-efficient, we mean that the energy consumption in delivering packets from source to destination is minimized. By power-aware, we mean that a route with nodes having higher residual (battery) power should be selected, although it may not be the shortest route.

In sensor networks, it is well-known that using clustering enables better resource allocation and helps improve power control [2]. Therefore, clustering is an energy-efficient architecture, wherein the individual nodes forward the information to their respective CHs. The information is aggregated at the CH and then sent to the BS by the CH. The CHs and BS usually form a multi-hop network, for which we propose a multi-hop routing protocol.

Recently, many researchers attempted to define specific sensor network architectures and provide power-aware routing protocols. In [3], the authors proposed an ad-hoc clustering protocol, the near term digital radio (NTDR), which includes a hierarchical routing algorithm based on a two-tier clustering without using low-energy routing or MAC. In [4], the authors directly aimed at minimizing the energy spent in the system by allowing d-hop clusters. In LEACH (Low-Energy Adaptive Clustering Hierarchy) [5], the nodes were organized into cluster hierarchies and TDMA was applied within each cluster. For a multi-hop routing protocol, energy efficiency can be improved in three areas: route setup, route maintenance, and service [6]. In [7], the authors proposed an energy-efficient routing to find the optimal paths based on two different power metrics: minimum energy per packet and minimum cost per packet. Another way to conserve energy is to use on-demand multi-hop routing algorithms, such as ADOV [8] and DSR [9], to eliminate most of the overhead associated with routing table updates. However, AODV has high energy cost during route setup or path discovery. In [6], the authors used a table-driven multi-path approach to improve the energy efficiency in a low-mobility network. In [10], the authors developed a protocol, directed diffusion, which employed a data-driven model to achieve low-energy routing. One of the methods to choose routes is to use minimum transmission energy routing [11], where intermediate nodes are chosen such that the sum of squared distances is minimized.

It is worthy pointing out that many of the existing sensor networking protocols have often applied data network concepts and produced inefficient algorithms. The significant differences in characteristics between a sensor network and a data network are: (a) Most traffic in sensor network is triggered by sensed events; (b) In reporting phase, the traffic goes from a hot-spot area, which consists of a few of the sensors, to a BS; (c) In polling phase, traffic goes from a BS to many sensors; (d) Many sensors coordinate for a common task and not all

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M. Yu and A. Malvankar are with the Department of Electrical & Computer Engineering, State University of New York, Binghamton, NY 13902. They can be reached via email at: {*mingyu,amalvankar1*}*@binghamton.edu.*

W. Su is with the CERDEC, RDECOM, Fort Monmouth, NJ. He can be reached via email at: Email: *wei.su@us.army.mil.*

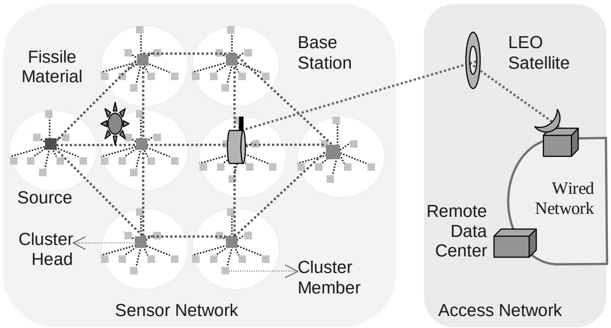

Fig. 1. Architecture of Sensor-Based EMS

of them must be active. Therefore, a sensor network is more like the fault management system (FMS) of a data network rather than the data network itself. For this reason, we propose the SEERA and port many FMS concepts and protocols to sensor networks, such as event routing, reporting, processing, correlation, by using SNMP (Simple Network Management Protocol) traps and alarms.

II. System Architecture

In an EMS, the typical application of a sensor network, the routed event can be either an anomaly event autonomously sent out by sensors, or a polling command issued by the remote collection stations. The proposed SEERA adopts a two-tier hierarchical clustering architecture which includes an adaptive clustering technique and multi-hop routing protocol.

• SEERA is based on an adaptive clustering technique. By monitoring the received signal power from other nodes, each node computes its optimal probability of becoming a CH. The clusters are formed in order that both the intra- and inter-cluster communications require the lowest amount of transmission power.

• In tier-1, SEERA functions as a new hybrid MAC protocol that consists of both contention and schedule. The cluster member nodes contend for a fixed number of slots or fame length. The slot allocations are scheduled based on Binary Countdown protocol [12].

• In tier-2, SEERA functions as a lightweight multi-hop routing protocol, which combines the on-demand routing protocols such as AODV [8] and energy-efficient routing protocols [7], which was called power-aware routing. The optimal route is chosen based on the energy consumption and residual power at each node along the route.

• SEERA also includes a feasible solution to the most possible and direct attacks that the routing protocol has to defend in an EMS, which have been identified as data and routing information tampering.

• Moreover, SEERA also defines a set of event reporting and correlation mechanism, which are ported from traps and polling events in FMS.

The architecture is shown in Fig. 1.

The focus of this paper is to present the adaptive clustering technique and the multi-hop routing protocol used in SEERA.

III. Adaptive Clustering

As the authors pointed out [5], the LEACH clustering method assumed that the number of nodes in the network and the optimal number of clusters to be formed were parameters that could be programmed into the nodes a priori. Actually, in a dynamic sensor network, old nodes may die out and new nodes may join. Thus, LEACH may not work well in dynamic networks. Recently, an improvement based on LEACH clustering, called HEED (Hybrid Energy Efficient Distributed) clustering, has been proposed in [4] to avoid the relying of the parameters on the number of active nodes. It must be pointed out that the selection of a CH is based on the node degree cost, which still needs to know the number of active nodes. Moreover, as the authors realized, HEED could not guarantee the optimal selection of CHs in terms of energy.

Therefore, the critical problem is how to estimate the parameters in real-time, which includes the number of active nodes and optimal number of clusters.

A. Real-Time Estimation of Number of Nodes

We assume that a sensor network is covered by a square area of side $2a$, thus the area $A = 4a^2$. Let's denote the number of sensors in the network is a random variable n. We assume that the sensors inside the area are distributed according to a homogeneous spatial Poisson process, with intensity of $\lambda\ sensors/m^2$. Hence, the mean value of n is λA. For a particular realization of the process there are N sensors in this area. We assume that the base station (BS) is at the center of the square area.

Let's define the probability of a node becoming CH as p. Thus, on average, there are Np nodes that will become CHs, the rest $N(1-p)$ nodes will be cluster members in total. The average number of CHs is denoted as k. Therefore, there are $k = Np$ clusters, each on average has $N/k-1$ member nodes.

To actively monitor the network status changes, such as the number of active nodes, we assume that each node keeps a record of the minimum power of the signals it has received within its radio range during previous cluster updating cycle. The record has only one value: the minimum signal power. Whenever the current value changes beyond a threshold value, the clustering updating process will be triggered. Therefore, we assume that each node is capable of measuring its received signal power. The measurement does not need to be an exact measuring because only relative comparison of the power is required. Also, the signal power sensed by each node is measured and compared locally to the node's record. Therefore, the resulting algorithm is a distributed scheme and the optimal probability of becoming a CH, p, is a local optimization, not a global one. This is reasonable because those nodes that are beyond the radio range of a node will not interfere with the node.

Let's denote the signal power a node has received by S. With our two-tier hierarchical clustering architecture shown in Fig. 1, each node within a cluster communicates to its CH by one hop distance. Let's denote the distance of a node to its CH as r. Within a cluster, we assume that the free space model is used:

$$S(r) = \epsilon_0/r^2, \ \ r \leq r_{max}, \tag{1}$$

where ϵ_0 is a constant related to the radio transmitter power and propagation environments; and r_{max} is the maximum allowable distance between a node and its CH.

In order to ensure that the probability of all the member nodes being within one hop distance from a CH is very high, we define a cell that covers most of the nodes in a cluster, which has been called a Voronoi cell [13]. Assume that the minimal ball that covers the Voronoi cell has a radius ρ_m, and the ball is centered at the nucleus of the cell. The probability that ρ_m is greater than a certain value ρ has a upper bound:

$$Prob\{\rho_m > \rho\} \leq 1 - [1 - \exp(-\mu p\lambda\rho^2)]^7, \tag{2}$$

where $\mu = 2(\frac{\pi}{7} + \sin\frac{\pi}{14} + \cos\frac{5\pi}{14})$, and $p\lambda$ is the equivalent intensity for the point process that describes the CHs. Eq. (2) can be simplified as:

$$Prob\{\rho_m > \rho\} \leq 7\exp(-\mu p\lambda\rho^2). \tag{3}$$

In order to ensure that the probability of all the member nodes being beyond the minimal ball is very low, we define a parameter, called degree of clustering (DoC), denoted as α, that

$$Prob\{\rho_m > \rho\} = \alpha, \tag{4}$$

where α is a very small value specified from cluster design requirement.

By combining Eqs. (3) and (4), we have

$$\alpha \leq 7\exp(-\mu p\lambda\rho^2). \tag{5}$$

By some manipulations, we can find such ρ that must meet

$$\rho^2 \geq -\ln(\alpha/7)/(\mu p\lambda). \tag{6}$$

In this way, the minimal ball covers most of the nodes in the Voronoi cell. Or equivalently, the maximum distance of a node to a CH must be bounded by Eq. (6) in order to fall inside the ball, that is,

$$r_{max}^2 \leq -\ln(\alpha/7)/(\mu p\lambda). \tag{7}$$

As we mentioned, almost all the nodes are within one hop distance from a CH. Therefore, we can let r_{max} take the maximum value, i.e., the equal sign in Eq. (7) holds. By substituting Eq. (1) into Eq. (7), we can find

$$S_{min} = -\frac{\epsilon_0\mu p\lambda}{\ln(\alpha/7)}, \tag{8}$$

where $S_{min} = \epsilon_0/r_{max}^2$ is the minimum signal power a node has received. Therefore, we can approximately estimate the value of the number of active nodes, by using $N = \lambda A$, if the probability of a node becoming CH, i.e., p value, is given.

It has been found in [4] that the optimal p value, denoted as p_{opt}, is the real root of the equation

$$cp_{opt}^{3/2} - p_{opt} - 1 = 0, \tag{9}$$

where $c = 4c_0a\sqrt{\lambda} = 2c_0\sqrt{N}$, and $c_0 = \frac{1}{2}(\sqrt{2} + \ln(\sqrt{2}+1))$, which is related to the average distance of a node to the BS located in the network center. By combining Eq. (8) and (9), after some rearrangements, we have

$$(c_1S_{min} - 1)p^2 - 2p - 1 = 0, \tag{10}$$

where $c_1 = -4c_0^2A\ln(\alpha/7)/(\epsilon_0\mu)$. The only real root of Eq. (10) is

$$p_{opt} = 1/(\sqrt{c_1S_{min}} - 1). \tag{11}$$

Now, it's clear that each node can independently calculate its optimal probability of becoming a CH based on its recorded minimum signal power.

Assume that during the jth cluster updating cycle, the measurement of S_{min} is denoted as $\tilde{S}_{min}(j)$, the corresponding value of p_{opt} as $\tilde{p}_{opt}(j)$. By using Eq. (8), we can find

$$\tilde{N}(j) = -\frac{\ln(\alpha/7)A\tilde{S}_{min}(j)}{\epsilon_0\mu\tilde{p}_{opt}(j)}, \tag{12}$$

where $\tilde{N}(j)$ is the calculated value of N in the jth cluster updating cycle.

During the $(j+1)$th cluster updating cycle, these measurement values will be used to obtain the estimation of N, which is denoted as $\hat{N}(j+1)$. To obtain smooth estimation, we use a moving averaging model:

$$\hat{N}(j+1) = \beta\hat{N}(j) + (1-\beta)\tilde{N}(j+1), \tag{13}$$

where $0 < \beta < 1$ is a smoothing factor used to adjust the estimation speed and accuracy. In our simulation, we find that $\alpha = 0.9$ is a good compromise between accuracy and promptness.

The optimal number of clusters can be easily obtained

$$\hat{k}_{opt}(j+1) = \hat{N}(j+1)\tilde{p}_{opt}(j+1). \tag{14}$$

Note that corresponding to Eq. (12), the probability of becoming CH, expressed in Eq. (11), can be also computed in terms of the measurement $\tilde{S}_{min}$:

$$\tilde{p}_{opt}(j+1) = 1/(\sqrt{c_1\tilde{S}_{min}(j)} - 1). \tag{15}$$

It can be seen from Eq. (15) that to compute the probability, each node does not need to know any network parameters a prior, nor rely on broadcast messages from the other nodes. It makes completely autonomous decisions based on its observed signal power levels. The parameters N and k are estimated in real-time by each node in a distributed way. Therefore, the proposed adaptive clustering approach scales well for dynamic and large-scale sensor networks. Moreover, the cluster formation and the selection of CHs are locally optimized in terms of energy.

B. The Adaptive Clustering Algorithm

In SEERA, each node actively monitors its received signal power levels during the cluster updating cycles, which can be specified high-level applications in terms of network requirement. To save energy consumption, the updating process can be triggered by some serious changes in network status, although computation consumes much less energy than communications. To trade off energy consumption and the adaptivity to network changes, we propose to tune the cycle time in terms of specific energy consumption model.

The adaptive clustering algorithm can be outlined as follows:

1. Specify the value of α, such as $\alpha = 0.001$. Initially, each node can be assigned with an initial value $p(0)$ for the probability of becoming CH. Because the initial value $N(0)$ is known, $p(0)$ can be computed optimally from Eq. (9) for all the nodes. And set $j = 1$.

2. Each node measures the power levels of the signals it has received from all its neighbors within the radio range. By simple comparison, only the minimum value $S_{min}(j)$ is recorded for the current cycle.

3. Each node computes its optimal probability of becoming CH in terms of Eq. (15).

4. Each node computes its estimation of the number of active nodes in the network by using Eqs. (12) and (13). Also, computes the optimal number of clusters by using Eq. (14). These values are used by high-level protocols to decide whether or not to conduct a cluster updating cycle.

5. Assume that each node can decide whether or not to activate updating process by checking the inequality:

$$|\hat{N}(j) - \hat{N}(j-1)| \leq \delta. \tag{16}$$

where δ is a predefined constant that determines the QoS requirement of the network. If Eq. (16) holds, don't activate a cluster updating process. Go to step 2, to monitor the network status. Or it does not do anything and simply wait for some specified event.

6. The node adopts the optimal probability $p_{opt}(j)$ and tries to become a CH with this new probability.

7. Let $j = j + 1$, go to step 2.

It is worthy noting that we are not trying to develop a global optimization solution to energy efficiency because of the complexity of the problem. In the above algorithm, each node attempts to find and stay at its optimal cluster locally. The algorithm is carried out by all nodes simultaneously and independently. In the times of no serious changes detected, the algorithm is aborted silently. If the changes exceeds some predefined threshold level, the node automatically adjusts its cluster to adapt to the changes in real-time.

IV. Multi-hop Routing

In SEERA, the CHs form a multi-hop network, in which the base station is usually multiple hops away from the reporting CH. One solution is to use a table-driven approach to improve energy efficiency in a low-mobility network [6], in which each node needs to have multiple paths to the base station. Another solution is to use location-based routing [14], in which the locations of the sensors need to be known to each other. In SEERA, we improve the cost during route setup by taking two measures: first, we use a two-tier hierarchical architecture so that the route setup is only limited to tier-2 network that consists of the CHs, which has a much smaller size than the flat structured network. Second, by using both energy-efficiency and power-awareness metrics, similar to the minimum energy per packet and minimum cost per packet proposed in [7], we develop an energy-efficient and power-aware routing protocol.

We assume that each node can estimate the power level in transmitting a packet, as in [15], [16]. The power level can be recorded into the packet format so that a neighboring node can compute the channel attenuation when receives the packet. In Section III, we assume that the radio transceiver of each node is capable of estimating the received signal power. Thus, the channel attenuation is simply the difference of the transmitted and received power.

Denote as S_i^t the power used to transmit a packet by a node i and S_j^r the power received by a node j. Then the power attenuation over the hops from i to j is

$$A_{i,j} = S_i^t - S_j^r, \quad i, j \in N_{CH}, \tag{17}$$

where N_{CH} is the set of CHs. Denote the set of paths from a source node sn to the BS node bs as $P = \{p : sn \rightarrow bs\}$. For a path $p \in P$, the path attenuation can be obtained

$$A_p = \sum_{i,j \in p} A_{i,j}, \quad p \in P, \tag{18}$$

where i and j are two neighboring nodes along path p.

Let's denote as B_i the new battery power of a node i. The accumulated power consumption of the node is denoted as C_i. Then the remaining battery power of the node is $B_i - C_i$. Consider both the power consumption and battery life requirements, a combined cost function can be chosen as:

$$D_p = \gamma \sum_{i \in p} \frac{C_i}{B_i - C_i} + (1-\gamma) A_p, \; p \in P, \tag{19}$$

where $0 < \gamma < 1$ is a coefficient used to weight between the two requirements: power-aware and energy-efficient.

Now the energy efficient routing problem can be written as:

$$\text{minimize} \sum_{\text{path } p} D_p, \; p \in P, \tag{20}$$

subject to the constraints:

$$B_i - C_i \geq S_{min}, \quad i \in \text{path } p, \tag{21}$$

where S_{min} is the minimum power required for a node to receive a packet correctly.

To find a global optimal solution by solving Eqs. (20) and (21), a source node, which can be possibly any one of the CHs, needs to communicate to all the other nodes and conducts intensive computation. This is not practical for a large-scale sensor network, because a sensor node only has limited computing and battery power.

In this paper, we develop a destination-assisted routing algorithm that solves Eqs. (20) and (21) by a BS. The BS selects multiple routes as candidates and gives each route a power consumption index (PCI), that is, a number to represent the total power consumption along the route, which has been collected by the BS. The BS informs each node along each of multiple possible routes the index value. The BS does not choose a final route because it does not know the battery life of a local node. It is the responsibility of each node to make a choice of its best route or energy-efficient route to the destination. The BS also observes and collects the total energy consumption of the network by accumulating energy consumption information from each node. In this way, the BS calculates a current reference value (CRV) to indicate the average remaining battery power of a node. The CRV is also sent to each node along a candidate route.

The routing algorithm in SEERA has been implemented similarly to AODV, which has four procedures: route discovery, forward path setup, route maintenance, and local connectivity management. We modify the first two procedures by incorporating the power consumption and battery life metrics into the route selection procedures.

In the route discovery procedure, a node sends out a route request message (RREQ) when the node wishes to send data to the BS, The RREQ message is flooded to other nodes. Each node piggybacks a transmitting power value in the RREQ message when relays the messages. By estimating the received power, each node can compute the various channel attenuations between itself and its neighbors. The node also updates its cache with the various routes and keeps the information up to date. The route is considered to be established when either the RREQ message reaches the final destination or an intermediate node, which has a route to destination in its cache. Based on Eqs. (17) and (18), the BS calculates the total power consumption for each route and assigns a PCI for each route. By adding all the consumed power from each node and dividing it by the total number of nodes in the network, the BS finds a value to indicate the average battery life, which is called CRV.

In the forward path setup procedure, the BS sends back a route reply message (RREP) to the originator of the RREQ message. One modification we made is to piggyback the PCI value for each route and the updated CRV into the RREP message, in addition to the modification in [15], which makes the protocol to generate multiple routes by replying multiple RREQ messages. The BS selects multiple routes by comparing the total power consumption of each route. The nodes on the multiple candidate routes are all informed of these values. When a node forwards a RREQ it also caches a route back to the originator. The PCI and CRV values are also obtained by these forwarding nodes. Once the source node receives the RREP message from various nodes, it updates its routing table. The best route is selected among the candidate routes in terms of Eq. (21) in which the S_{min} value is replaced by the CRV.

If any node in the selected route does not have enough battery power, the route is discarded. Then, the next best route is selected in terms of the PCI. If more than one route meet the criteria of CRV, then the one has the lowest PCI value is selected. This case happens when the event traffic in some of the network is not balanced so that the CRV does not reflect the remaining battery power of the local nodes. This procedure is continued until a final route is found. If no such route exists, then the CRV has to be adjusted by reducing some percentage, which is depending on a predefined unit in the operation. Finally the route selected is power-aware as well as energy-efficient.

The route maintenance and local connectivity management procedures are the same as in AODV, which are used to manage the link status and time validity of a path and to inform its neighbors the aliveness of a node. If a route becomes invalid or if some node on the route fails, the maintenance and local connectivity management procedures are responsible to issue a route error (RERR) message to notify all the nodes about the failure of the route.

Compared to the existing power-aware and energy-efficient routing algorithms, the proposed routing algorithm has the following advantages. First, a sensor node does not need to record the total power to reach the BS, as in [15]. Second, intensive communications and computation have been avoided by a sensor node, not to say the location information [14]. Third, both the power consumption and battery life requirements have been considered without relying a radio propagation model, which needs distance or location information. The algorithm in [15] does not consider the battery life requirement. The algorithms in [14], [16] consider both requirements by using radio propagation models, which are highly depending on the deployment environment and can be vastly different. Fourth, the proposed algorithm is a destination-assisted routing algorithm that only the BS involves most of the computation and selects the candidate routes, although the routing request is initiated by a source node.

It is worthy noting that the proposed algorithm is only a local optimization method. The complexity of the routing problem in Eqs. (20) and (21) has been greatly reduced, although the solution may be not globally optimal.

V. Simulation Results

In this section, we conduct our simulation studies for two example sensor networks, with an architecture shown in Fig. 1, and compare our results to those reported in [4], [5], [17].

A. Example Network 1

The parameters use the same values as in [4]. We assume that the sensor network is used to cover a square area of side $2a = 10\ m$, and the area $A = 100\ m^2$. The BS is assumed at the center of the square area. We assume that the sensors inside the area are distributed according to a homogeneous spatial Poisson process, with an unknown intensity of λ. Hence, the average number of sensors in the network, $N = \lambda A$. The probability of a node is beyond one-hop distance from a CH is $\alpha = 0.001$, which means only one-tenth of a percent of the total nodes will not join any clusters and become single node cluster. We assume the free space propagation model with coefficient $\epsilon_0 = 1$ for simplicity. The measured minimum received signal powers are $S_{min} = 0.0746$, 0.1244, 0.1288, 0.1639, 0.2018, and 0.2002, respectively. These values contain a 50% of measurement errors that are represented by White Gaussian noise, compared to the real values of the intensity of the Poisson process, $\lambda = 5$, 10, 15, 20, 25 and 30 $sensors/m^2$, respectively. Or equivalently, the average numbers of sensors in the network are $N = \lambda A = 500$, 1000, 1500, 2000, 2500, and 3000, respectively.

To verify the correctness of the proposed real-time estimation algorithm, the estimated N values are in Fig. 2. Compared to the analytical values of N, we can see that the estimation algorithm has a good accuracy. Even in the cases of a 50% of measurement errors, the resulting relative errors of estimation

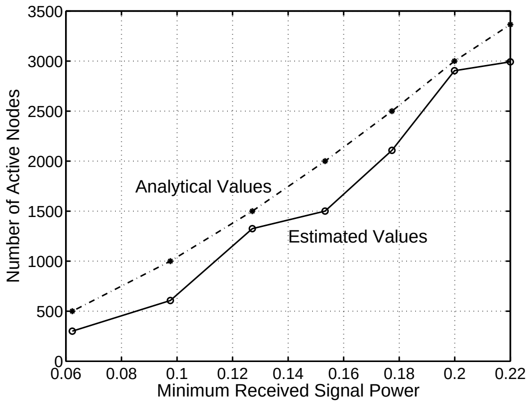

Fig. 2. Number of Nodes and Minimum Signal Power

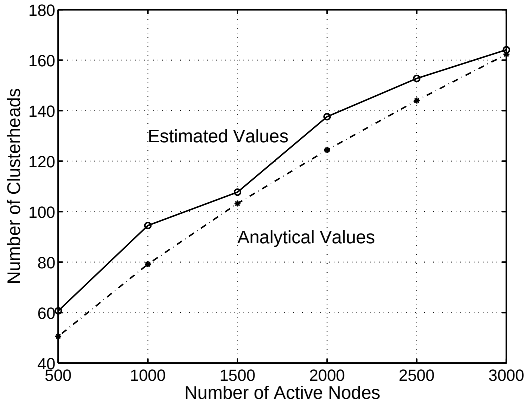

Fig. 3. Numbers of Clusters and Nodes

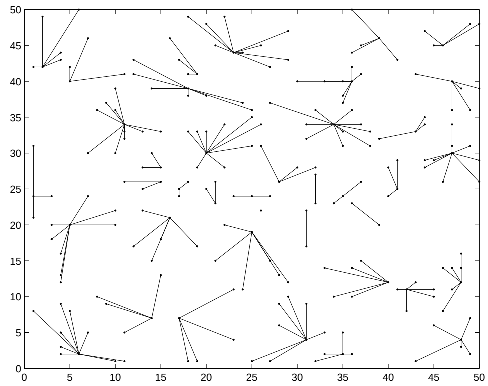

Fig. 4. A Clustering Senario

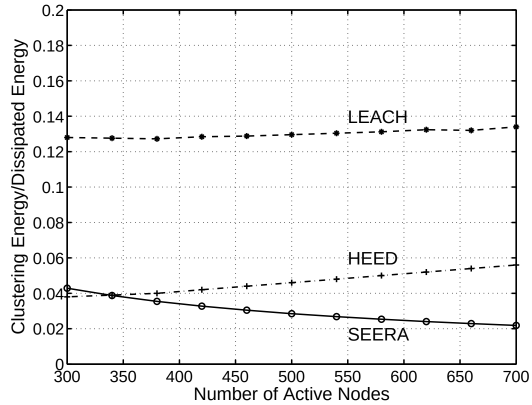

Fig. 5. Ratio of Clustering Energy to Total Energy

on the number of active nodes are in the range of $5 \sim 15\%$. The optimal number of clusters in the network, as shown in Fig. 3, is also very close to the analytical values.

During the simulation, it has also been noticed that the real-time algorithm is able to generate a stable estimation of the $\hat{N}$ values within about $5 \sim 6$ iterations, by starting from an initial value that is close to the initial number of active nodes, which is given in practice. If the initial number of active nodes is unknown, by starting from a random probability of becoming CH, the number of iterations on average is around 10. Therefore, the estimation algorithm converges fast as we expect.

B. Example Network 2

In this example, the parameters use the same values as those in [17]. The network is assumed to have $N = 300 \sim 700$ nodes that are uniformly dispersed into a square area of $A = 10000\ m^2$. The BS is located at the right side of the area, with a distance of $125\ m$ to the center of the square.

The values of these parameters are: $d_0 = 75\ m$, $E_{elec} = 50\ nJ/bit$, $\epsilon_{fs} = 10\ pJ/bit/m^2$, $\epsilon_{mp} = 0.0013\ pJ/bit/m^4$, $E_{fusion} = 5\ nJ/bit/signal$, $DP_{size} = 100\ bytes$, $BP_{size} = 25\ bytes$, $PKT_{hdr} = 25\ bytes$, $T_{cluster} = 5\ TDMA\ frame$, and $E_{battery} = 2\ J/battery$.

To verify the energy efficiency of the proposed adaptive clustering technique, we apply the same algorithm used in Examples 1 and 2. The clustering result is shown in Fig. 4. The ratio of the energy spent in clustering is plotted vs. the total energy spent in the network in Fig. 5. It can be seen that the proposed SEERA clustering process consumes much less energy than the one used in LEACH [5]. It is also less than HEED [17], especially when the number of nodes is large, the energy reduction is more obvious. For example, when the number of active nodes is 700, the SEERA clustering reduces the energy consumption more than 50%. Clearly, SEERA works well for large-scale sensor networks, because the probability of a node becoming CH is optimized and the each node makes decision to become CH in a distributed fashion.

To demonstrate the effectiveness of the proposed adaptive clustering algorithm in prolonging the network lifetime, we plot the network lifetime, which is measured by the time either the first node becomes inactive or the last node becomes inactive, vs. the number of active nodes in the network in Figs. 6 and 7, respectively. From these two figures, we can see that SEERA outperforms LEACH in network lifetime measured by both the first and last nodes become inactive. The network lifetime achieved by SEERA is comparable to HEED, depends on the cluster updating cycles and number of nodes in the network. In this example, we use $T_{cluster} = 5$ TDMA frame, which means the cluster updating is so frequent that the clustering setup cost is high. The reason is that the estimated

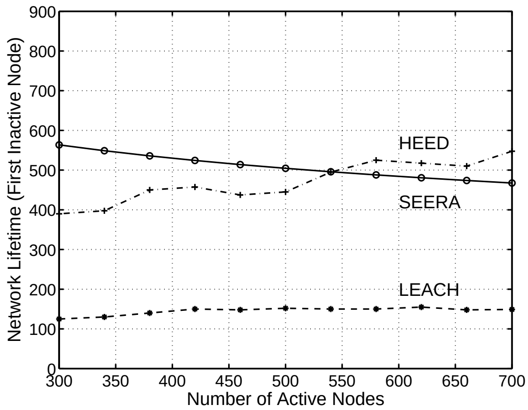

Fig. 6. Network Lifetime Until First Node Inactive

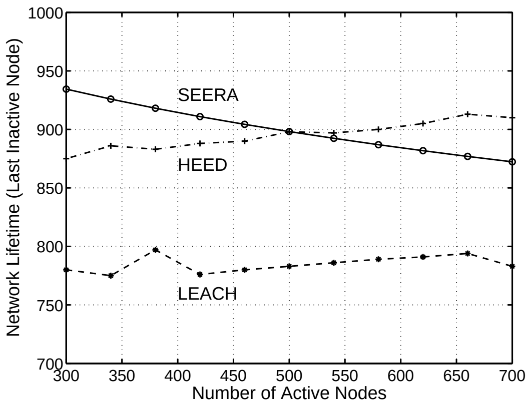

Fig. 7. Network Lifetime Until Last Node Inactive

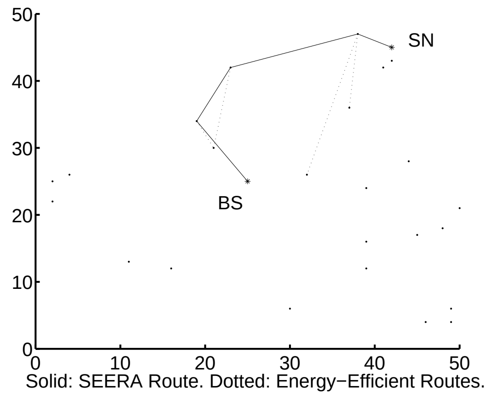

Fig. 8. Energy-Efficient and Power-Aware Routing Scenario 1

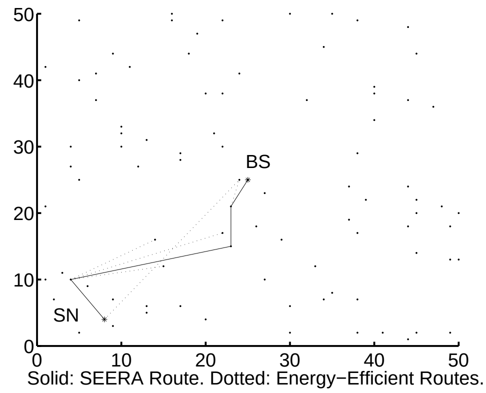

Fig. 9. Energy-Efficient and Power-Aware Routing Scenario 2

number of active nodes does not reach a stable and optimal value, especially when the initial value in the estimation is randomly selected. On the other hand, the HEED clustering uses a fixed value for the probability of becoming clustering and the number of clusters uses an initial value that is very close to the optimal value, as reported in [17]. Therefore, a high percentage of the total energy is used in the cluster formation process in SEERA. If a longer cluster updating cycle were used, the ratio of the total energy expended in cluster formation process would be lowered, as shown in Fig. 5.

In Fig. 8, the route needs to be established is between a source node (SN) located at $(40, 45)$ and the BS at $(25, 25)$. The final route is shown in solid line and the possible routes in each hop are shown in dotted lines, which are possible routes that could be taken if the routing algorithm was not power-aware. The possible routes are only energy-efficient, not power-aware, which means that the nodes on these routes do not meet the minimum power requirements. Therefore, they are not chosen for the final route. After the next hop is chosen, the dotted lines indicate the possible routes that could be taken from that hop. This procedure continues until the BS is finally reached. For a higher node intensity, a similar route is shown in Fig. 9 between SN and BS, which are CHs. As battery power decreases, some nodes are not available for routing. Thus, the dynamic clustering alogrithm is triggered to rediscover the network topology. Figures 10 and 11 show the reclustered tier-2 network, with routes established between SN and BS.

Thus, SEERA still outperforms the existing clustering techniques and energy-efficient routing algorithms.

VI. Discussion and Conclusion

A. Discussion

The SEERA architecture and protocols proposed in this paper are developed for a general class of environment monitoring systems based on networked sensors. The event routing concept and adaptive clustering technique are the critical parts in SEERA. There are some assumptions are worthy to be further discussed.

We assume that the sensors are capable of comparing the power levels of the received signals and thus keeping track of the minimum signal power levels. In the case that the sensors are very simple device that could not make difference among received signal power levels, the applications of the proposed clustering technique would be restricted. We may either have to increase the capability of the sensors, or investigate alternative methods to estimate the number of active nodes in the network. One such method may be estimating the average number of active nodes in terms of the average signal power by using a relationship between the node distribution and cell radius [13].

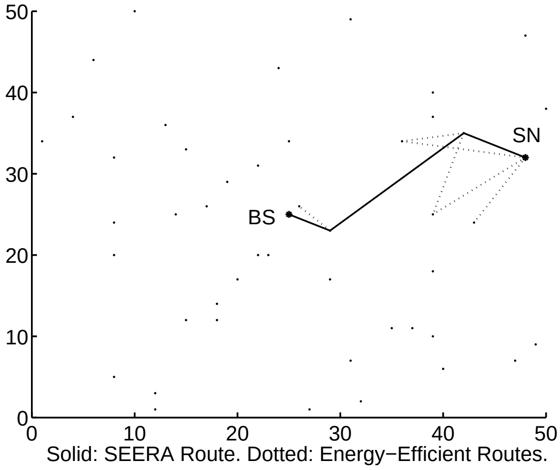

Fig. 10. Energy-Efficient and Power-Aware Routing Scenario 3

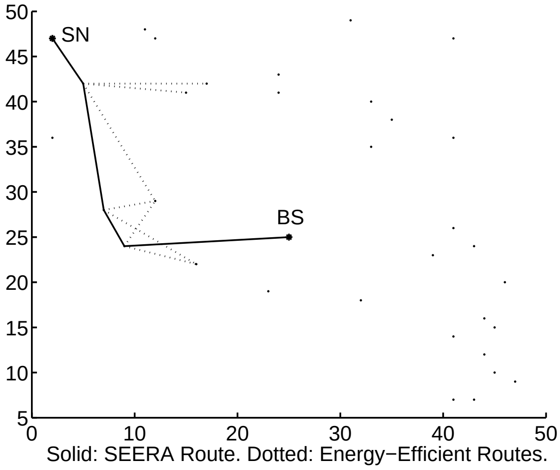

Fig. 11. Energy-Efficient and Power-Aware Routing Scenario 4

We also assume that the sensors in the network are distributed according to a homogeneous spatial Poisson process. For heterogeneous node distribution, the estimation of the number of active nodes and thus the computation of optimal number of clusters and the probability of becoming CHs need to be extended. The proposed local optimization scheme may not be optimal in terms of energy efficiency. Moreover, we need to find a globally optimized solution to the estimation problem if it exists.

In the event routing, we assume that channel utilization in sensor networks is only a secondary goal, and each node can randomly select a frequency band from a large pool of possible frequency bands. For a large-scale sensor network, this assumption may be too strong for practical applications. In this case, we can consider a dynamic channel allocation technique that a few clusters may have to share the same frequency bands. The related problems such as latency, throughput and fairness will have to reconsidered.

B. Conclusion Remarks

In this paper, we present a networking protocol that includes an adaptive clustering technique, and an energy-efficient and power-aware multi-hop routing algorithm, for large-scale sensor networks.

The simulation results have demonstrated that the two-tier hierarchical architecture with the adaptive clustering technique and routing algorithm adapt to changes in network topology, scale well to large network sizes, and are energy-efficient.

Our future work would be further investigating the applicability of the proposed technique and algorithm to a larger number of other applications of sensor networks.

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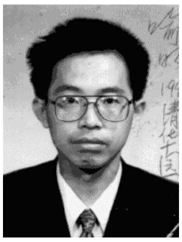

Ming Yu received his Doctor of Engineering from Tsinghua University, Beijing, in 1994, and Ph.D. from Rutgers University, New Brunswick, NJ, in 2002, all in Electrical and Computer Engineering.

He joined the Operation Technology Center, AT&T, Middletown, NJ, in July 1997 as a Senior Technical Staff Member. Since 1999, he was with the Dept. of ATM Network Service, AT&T Labs, Middletown, NJ. From December 2002, he worked for the Dept. of IP/Data Network Management System Engineering, AT&T Labs. As of August 2003, he joined the Dept. of Electrical and Computer Engineering, State University of New York, Binghamton, NY, as an assistant professor.

His research interests are in the areas of routing protocols, MAC, QoS, network security, energy-efficiency, clustering, radio resource management, traffic engineering, and performance analysis, for both wired and wireless networks.

Dr. Yu is a senior member of the IEEE. He was awarded the Third IEEE Millennium Medal by the IEEE on May 2000.

Aniket Malvankar received his B.S. degree in electrical engineering from Bombay University, India, in 2002, and M.S. degree in electrical and computer engineering from State University of New York at Binghamton in 2005. Currently, he is a Ph.D. student in the Department of Electrical and Computer Engineering, State University of New York at Binghamton.

His research interests are wireless ad hoc networking protocols, energy-efficient routing protocols, mobility modeling, radio resource management, and communication systems.

He is a student member of the IEEE.

Wei Su received the B.S degree in electrical engineering and the M.S degree in systems engineering from Shanghai Jiao Tong University, China, in 1983 and 1987, respectively. He received his Ph.D. degree in electrical engineering from The City University of New York, New York, in 1992.

He joined the Army Research Laboratory, at Fort Monmouth, New Jersey in 1994 as an electronics engineer. Since 1998, he is with the U.S. Army Communication Electronics Research Development and Engineering Center, at Fort Monmouth, New Jersey as a senior technical staff and project leader. His research interests include communication intelligence, signal and image processing, and automatic control.

He was a recipient of 2002 Thomas Alva Edition Patent Award, a recipient of 2004 AOC International Research and Development Award, and a recipient of 2005 Army Research and Development Award. He is a Senior Member of IEEE.