A Dynamic Clustering and Energy Efficient Routing Technique for Sensor Networks

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***Abstract*— In the development of various large-scale sensor systems, a particularly challenging problem is how to dynamically organize the sensors into a wireless communication network and route sensed information from the field sensors to a remote base station. This paper presents a new energy-efficient dynamic clustering technique for large-scale sensor networks. By monitoring the received signal power from its neighboring nodes, each node estimates the number of active nodes in real-time and computes its optimal probability of becoming a cluster head, so that the amount of energy spent in both intra- and inter-cluster communications can be minimized. Based on the clustered architecture, this paper also proposes a simple multihop routing algorithm that is designed to be both energy-efficient and power-aware, so as to prolong the network lifetime. The new clustering and routing algorithms scale well and converge fast for large-scale dynamic sensor networks, as shown by our extensive simulation results.**

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

I. INTRODUCTION

RECENTLY, various sensor networks have been developed for a variety of applications, such as surveillance, environmental monitoring, and telemedicine [1]. A large-scale sensor network consists of a large number of small, relatively inexpensive and low-power sensors that are connected as a wireless network, through which the data extracted from the sensor nodes is sent to a remote base station (BS). The networking protocols must scale well to a large number of nodes, adapt to a dynamic network environment, be energy-efficient as well as power-aware. By energy-efficient, we mean that the energy spent on delivering packets from a source to a destination is minimized. By power-aware, we mean that a route with nodes currently having higher remaining battery power should be selected, although it may not be the shortest one.

It is well-known that a cluster architecture enables better resource allocation and helps to improve power control. It also scales well to different network sizes and node densities under energy constraints [2]. In a typical two-tier architecture, individual sensor nodes forward information to their respective cluster heads (CHs). At the CH the information is aggregated and then sent to a BS by the CH. The CHs and the BS usually form a multihop network, for which energy-efficient routing protocols need to be applied [3].

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II. RELATED WORK

The extensive work related to this paper can be categorized into energy-efficient clustering methods and multihop routing protocols.

A. Related Work in Clustering Methods

The clustering methods in sensor networks can be categorized into static and dynamic ones.

The static clustering methods aim at minimizing the total energy spent during the formation of the clusters for a set of given network parameters, such as the number of nodes in the network [2]. A problem that is closely related to the static clustering is the localized topology control, which maintains an energy-efficient network connectivity by controlling the transmission power at each node [4], or selecting a small subset of the local links of a node [5]. One way is to minimize the total power levels in all nodes and search for a connected topology [6]. Another way is to select a minimum set of sensors that form a connected communication graph to cover the entire network region, by iteratively searching for one path at a time and adding the nodes of the path to a set of already selected sensors [7].

The dynamic clustering methods deal with the same energy efficiency problem as the static ones but target for a set of changing network parameters, such as the number of active nodes or the available energy levels in a network [8]. In LEACH (low-energy adaptive clustering hierarchy) [3], the position of a CH was rotated among the nodes within a cluster depending on their remaining energy levels. It was assumed that the number of active nodes in the network and the optimal number of clusters to be formed were parameters that could be programmed into the nodes *a priori*. In [9], a genetic algorithm was proposed to form clusters in terms of a few fitness parameters such as the sum of all the distances from each sensor to the BS. In HEED (hybrid energy efficient distributed) clustering [10], a CH was selected based on the ratio of the node's residual energy to a reference maximum energy. But the optimal selection of CHs were not guaranteed in terms of energy consumption without knowing the number of active nodes in a network.

B. Related Work in Routing Protocols

Once the network architecture has been established by clustering, ad hoc routing protocols can be applied to improve the energy efficiency. For example, on-demand routing protocols, such as ADOV [11], can be used to eliminate most of the overhead associated with routing table updates. However, they have high energy cost during route setup.

Generally, an energy-efficient routing problem can be formulated as a classical optimal routing problem with energy constraints [12], if the energy expenditure in each stage of routing can be obtained. The objective is to maximize the network lifetime, which can be the time until the first node dies out due to its energy depletion [13], or the number of successful data deliveries until a connectivity or coverage is lost [14]. The problem can be solved as a linear programming problem, for which gradient algorithms, heuristic algorithms, or other searching algorithms can be used to find optimal routes [15], [16].

It is worth pointing out that the routing metrics used in the energy-efficient routing play a major role in optimizing the network performance. In [17], two different power metrics were proposed: minimum energy per packet and minimum cost per packet. In [18], a more general link cost was proposed, which included the energy expenditure in a transmission and receiving, the initial and the residual battery power of a node. The routing metrics used in the minimum total energy (MTE) routing [3] and the maximum residual energy (MRE) routing [18] can be expressed as special cases of the link cost function. But how to select good exponents for the energy expenditure and battery power is unknown.

In this paper, we propose to directly estimate the number of active nodes in a network [19], [20]. Based on the estimation, we develop an energy-efficient and dynamic clustering (EEDC) technique by minimizing the total energy consumptions in the network. We also propose a simple routing metric that is composed of the energy expenditure and battery power of a node. Based on the metric, we develop a routing algorithm that is energy-efficient and power-aware (EEPA).

The remainder of this paper is organized as follows. Section III describes the algorithm to estimate the number of active nodes and the dynamic clustering technique. Section IV presents the multihop routing algorithm. The simulation results are presented in Section V. We conclude this paper in Section VI.

III. Dynamic Clustering Based on Measurement

A. Network Model

The architecture of our sensor network is shown in Fig. 1, in which a two-tier hierarchy is adopted. The area of the network is $|A| = 4a^2$. All the sensors in the network area are clustered into different clusters. In the phase of cluster formation, each node tries to become a CH with a certain probability by wining a competition with its neighbors. In the phase of data collection, each cluster member (CM) communicates to its CH directly by using a MAC layer protocol, such as the p-persistent CSMA in the IEEE 802.11 standard. In the phase of data delivery, the CH in the hot-spot area aggregates the data received from its CMs and then delivers the aggregated data hop-by-hop to the BS by using a multihop routing protocol.

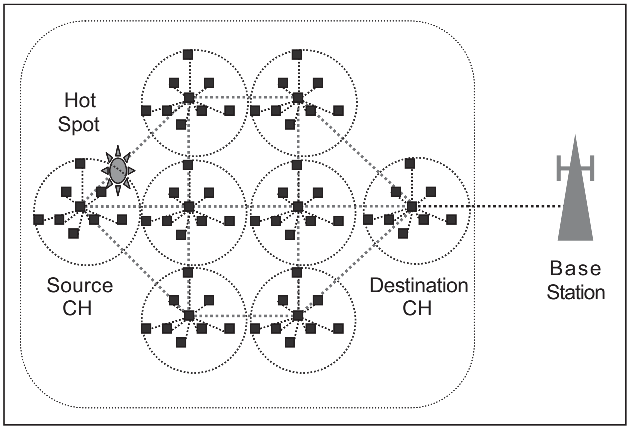

Fig. 1. The architecture of a clustered sensor network.

With the two-tier clustering architecture, the cost during route setup is improved because routing is only limited to the CHs or tier-2 network, which has a much smaller size than the flat structured network.

We assume that each sensor node can detect the signal strength within its radio range. Here, we only consider the active nodes, which are those that have enough energy to join or form a cluster. We assume that the sensors in the network are distributed according to a homogeneous spatial Poisson process, with an intensity of λ. The average number of sensors in the network is

$$n = \lambda|A|. \tag{1}$$

The probability of a node becoming a CH during clustering is denoted as q. On average, there are nq nodes that become CHs, the rest $n(1-q)$ nodes become CMs. Let's denote k the average number of CHs in the network and m the average number of CMs within a cluster. Thus,

$$k = nq, \tag{2}$$

$$m = n/k - 1 = 1/q - 1. \tag{3}$$

As nodes may join or leave the network (become inactive due to energy depletion), n in Eqn. (2) is a changing number, although its initial value may be given at the time the sensors are deployed. Therefore, we need to estimate n in real-time. Also, the value of q has to be determined in terms of the estimation of n and requirements on the energy efficiency.

B. Intra-Cluster: Formation of A Single Cluster

A widely used measurement-based radio propagation model is the path-loss model with log-normal shadowing [21]:

$$\frac{s_r}{s_t}(dB) = 10\log_{10}\kappa - 10\gamma\log_{10}\frac{r}{r_0} + \psi_{dB}, \tag{4}$$

where s_t and s_r are random variables that describe the powers of a signal a sensor node has transmitted and received at distance r, respectively; κ is a dimensionless constant which depends on the antenna characteristics and average attenuation from blockage, while r_0 is a reference distance from the antenna far-field; γ is the path-loss exponent; ψ_{dB}

is a Gaussian-distributed random variable with zero mean and variance σ_ψ, which can be also measured.

We assume that the parameters in Eqn. (4) are given for specific sensors and measured for specific application environment. By taking means on the random variables in Eqn. (4), we have

$$\frac{S_r}{S_t}(dB) = 10\log_{10}\kappa - 10\gamma\log_{10}\frac{r}{r_0}, \tag{5}$$

where S_r and S_t are the mean values of s_r and s_t, respectively.

To simplify the notation, in stead of using dB as unit, we rewrite the model as:

$$S_r = \epsilon_0/r^\gamma, \;\; r_0 \le r \le R, \tag{6}$$

where $\epsilon_0 = \kappa r_0^\gamma S_t$, which represents all the dependencies on the transmission power, antenna characteristics, and radio propagation environment. R is the radio range of the transceiver of the sensor. We also assume that $S_r = S_0$ for $r \le r_0$, i.e., no attenuation within the distance of r_0.

During the formation of a cluster in a region (or a part) of a network, we can choose a particular node in the region as a CH and all other nodes as the CMs, if all these CMs are closer to the CH than to any other nodes in the region. In mathematics, the topologically discrete set of these CM nodes in Euclidean space is the interior of a convex polygon in two dimensions (or polyhedron in three dimensions), which is called the Voronoi cell (or Dirichlet domain) of the CH.

In this section, we model the clustering by using the Voronoi cell, which is energy-efficient due to the fact that the formation of a Voronoi cell is based on the closeness of the CMs to the CH. Our goal is to ensure that there is a very high probability that all the CMs associated with a CH are within the radio range of the CH. In this way, most nodes are able to communicate to the CH directly for intra-cluster communications.

In terms of the results on Voronoi cell [22], the probability that the radius of a cluster, r, is greater than a certain value, r_a, has an upper bound:

$$p_{rob}\{r > r_a\} \le 1 - \left[1 - \exp(-\mu q\lambda r_a^2)\right]^7, \tag{7}$$

where $\mu = 2(\frac{\pi}{7} + \sin\frac{\pi}{14} + \cos\frac{5\pi}{14})$, and $q\lambda$ is the equivalent intensity for the point process that describes the CH of a cluster. Eqn. (7) can be simplified:

$$p_{rob}\{r > r_a\} \le 7\exp(-\mu q\lambda r_a^2). \tag{8}$$

We define a parameter, called degree of isolation (DOI), denoted as σ:

$$\sigma = 7\exp(-\mu q\lambda r_a^2), \tag{9}$$

where σ takes small value, such as 0.001, as shown in the simulation, which can be specified as a clustering requirement. A higher value of σ means that more nodes, up to a percentage of σ among the total number of nodes, will not be covered by any clusters, and thus have to stay alone. Thus,

$$r_a = \sqrt{\frac{-\ln(\sigma/7)}{\mu q\lambda}}, \tag{10}$$

which is the minimal radius for the cluster that can cover most of its CMs for a specific DOI.

Note that $\lambda = n/|A|$. The above equation can be rewritten as

$$r_a = c_1/\sqrt{nq}, \tag{11}$$

where

$$c_1 = \sqrt{-\ln(\sigma/7)|A|/\mu}, \tag{12}$$

is a constant for a given DOI.

By combining Eqns. (6) and (11), we have

$$S_a = \epsilon_0 c_1^{-\gamma}(nq)^{\gamma/2}, \tag{13}$$

where S_a is the signal power a node received at a distance of r_a. From the viewpoint of a CH, S_a is the minimum signal power it has received from its CMs, if we choose r_a as its radio range.

If the value of S_a is measurable, then we can estimate the number of clusters, in terms of Eqns. (2) and (13):

$$k = c_2 S_a^{2/\gamma}, \tag{14}$$

where

$$c_2 = \epsilon_0^{-2/\gamma}c_1^2 = -\frac{\ln(\sigma/7)}{\epsilon_0^{2/\gamma}\mu}|A|, \tag{15}$$

is also a constant for a given DOI. In terms of Eqn. (2), we have $q = k/n$, i.e., clusters can be formed only if n has been estimated, although k can be estimated by Eqn. (14).

C. Inter-Cluster: Formation of A Clustered Network

In the network level, the requirement on clustering is to have as less number of clusters as possible. As we see in the formation of a single cluster, another requirement is to have the CMs within a cluster as close to their CH as possible. Thus, we design a combined cost function, with weighting coefficients of ε_1 and ε_2, to measure the cost incurred by the two requirements, respectively:

$$C(q) = \varepsilon_1 k\frac{|D_1|}{H_1} + \varepsilon_2\sum_{j=1}^{k} m\frac{|D_2|}{H_2},$$

where D_1 is the average distance from a CH to the BS; D_2 is the average distance from a CM to its CH; and H_1 and H_2 are the hop distance of the CH and CM, respectively. The cost function can be rewritten as:

$$C(q) = e_1 k|D_1| + e_2\sum_{j=1}^{k} m|D_2|, \tag{16}$$

where $e_1 = \varepsilon_1/H_1$ and $e_2 = \varepsilon_1/H_2$.

The physical meaning of the cost function defined in Eqn. (16) can be explained as follows. We assume that the network needs to collect the information sensed by the nodes in the network and deliver it to the BS. First, there are k CHs in the network. For each of them, the major energy consumption is caused by delivering the information via $|D_1|/H_1$ hops to the BS. For per hop and per unit of information (e. g., one packet), the energy consumption is ε_1. Second, there are km CMs in the network. Similarly, ε_2 can be used to represent the average energy spent by a CM in delivering the information per packet per hop. Based on the interpretation, $C(q)$ in Eqn. (16) represents the total energy spent by the network to collect one unit of information and deliver it to the BS.

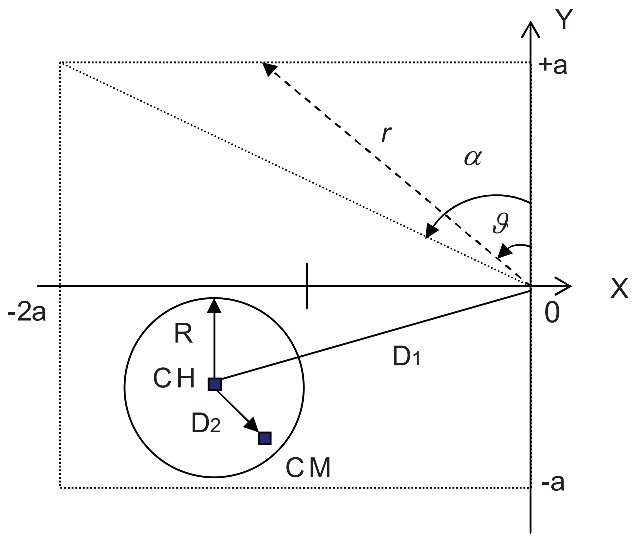

Fig. 2. Demonstration for calculating D_1 and D_2.

TABLE I
SIMULATION PARAMETERS AND VALUES

Parameters	Values	Comments
d_{th}	$75\ m$	threshold
γ_{fs}	2	for $d < d_{th}$
γ_{mp}	4	for $d \geq d_{th}$
ϵ_{fs}	$10\ pJ/bit/m^2$	for $d < d_{th}$
ϵ_{mp}	$0.0013\ pJ/bit/m^4$	for $d \geq d_{th}$
E_{elec}	$50\ nJ/bit$	energy for receiving
E_{fusion}	$5\ nJ/bit/signal$	energy for fusion
$DPkt_{size}$	$100\ bytes$	data packet
$BPkt_{size}$	$25\ bytes$	broadcast packet
Pkt_{hdr}	$25\ bytes$	packet header
$T_{cluster}$	$5\ TDMA\ frame$	clustering cycle
$E_{battery}$	$2\ J/battery$	initial energy

The calculations of D_1 and D_2 are shown in Fig. 2. For D_1, we have

$$\begin{aligned} D_1 &= \int_A r\frac{1}{|A|}rdrd\theta \\ &= \frac{2}{|A|}\Big[\int_0^{\alpha}\int_0^{\frac{a}{cos\theta}} r^2drd\theta + \int_{\alpha}^{\frac{\pi}{2}}\int_0^{\frac{2a}{sin\theta}} r^2drd\theta\Big] \\ &= d_0a, \end{aligned} \tag{17}$$

where r and θ are variables of the integral, $\alpha = \arctan 2$; and $d_0 = \frac{\sqrt{5}}{3} + \frac{1}{12}\ln(2+\sqrt{5}) - \frac{2}{3}\ln(\frac{\sqrt{5}-1}{2}) = 1.1865$.

Let's denote Ω the radio coverage area of a CH, with a radius of r_a from the CH to its furthest nodes. For D_2, we have

$$D_2 = \int_{\Omega} r\frac{1}{|\Omega|}rdrd\theta = \int_0^{2\pi}\int_0^{r_a}\frac{1}{\pi r_a^2}r^2drd\theta = \frac{2}{3}r_a. \tag{18}$$

Note that r_a in the above equation depends on k, which in turn depends on q, as in Eqn. (2). The reason is that the coverage area of a cluster on average becomes smaller if there are more clusters in the network area.

By substituting Eqns. (2), (3), (17) and (18) into (16), we have

$$C(q) = e_1d_0anq + e_2nq(\frac{1}{q}-1)\frac{2}{3}r_a. \tag{19}$$

By substituting Eqn. (11) into Eqn. (19), we have

$$C(q) = e_1d_0anq + e_2\frac{2c_1}{3}\sqrt{nq}(\frac{1}{q}-1). \tag{20}$$

To find an optimal q value that minimizes the cost $C(q)$, let $dC(q)/dq = 0$, and define a constant:

$$c_3 = \frac{3d_0a}{c_1}\frac{e_1}{e_2} = \frac{3d_0}{2}\sqrt{\frac{\mu}{-\ln(\sigma/7)}}\frac{e_1}{e_2}, \tag{21}$$

we have

$$c_3\sqrt{n}q^{3/2} - q - 1 = 0, \tag{22}$$

which is the same equation that was found in [2] with a different coefficient $\sqrt{2} + \ln\sqrt{2} + 1$. The solution depends on the number of nodes and other parameters, including the DOI, and the ratio of the two energy coefficients, i.e., e_1 and e_2.

By substituting Eqn. (2) for n into Eqn. (22), we have

$$\hat{q} = \frac{1}{c_3\sqrt{\hat{k}} - 1}, \tag{23}$$

where

$$\hat{k} = c_2\hat{S}_a^{2/\gamma}, \tag{24}$$

which is Eqn. (14) with S_a replaced by $\hat{S}_a$, the measurement of S_a. Thus,

$$\hat{n} = \hat{k}/\hat{q}, \tag{25}$$

where $\hat{k}$, $\hat{q}$, and $\hat{n}$ are the estimated values for k, q, and n, respectively. Clearly, clustering can be conducted based on the measured S_a value.

The values of e_1 and e_2 can be chosen as follows.

Assume that the average energy consumption in network layer for a CH to receive and transmit a unit of data (e. g., a packet) over a hop distance of $H_1 = H$ is $\overline{E}_{r1}$ and $\overline{E}_{t1}$, respectively. Note that an intermediate forwarding is counted as one receiving plus one transmission.

$$e_1 = (\overline{E}_{r1} + \overline{E}_{t1})/H, \tag{26}$$

where $\overline{E}_{r1} = E_{elec}$; E_{elec} is the energy spent in electrical device for receiving a unit of data; and $\overline{E}_{t1} = E_{elec} + \epsilon_0H^{\gamma}$, ϵ_0 and γ take different values in free space (e.g., ϵ_{fs} and γ_{fs}) and multipath models (e.g., ϵ_{mp} and γ_{mp}), depending on the values of H (e.g., d), as defined in Table I.

Note that in Eqn. (26), $\overline{E}_{t1}$ is not related to distance. There are two reasons to do so. First, optimizing $\overline{E}_{t1}$ does not result in much saving over one hop distance. Second, we want to isolate the design issues in MAC and network layers so as to simplify the design.

The average energy spent in MAC layer for a CM to deliver a unit of data to its CH can be calculated as follows. In one virtual transmission time (VTT), which is defined as the time interval between two successful transmissions [23], the CM spends an amount of time on one successful transmission, some time on collision, and some time on idle. The lengths of the three times, denoted as w_s, w_c, and w_i, can be computed in terms of the number of nodes participating in a MAC competition, i.e., m, and the probability that a node transmits a packet at the beginning of an empty slot, i.e., p_m. As an example, the computations of these parameters for the IEEE 802.11 MAC are given in detail in [24].

Assume that the average energy consumption in MAC layer for a CM is $\overline{E}_{r2}$ for receiving data per time unit (e. g., a time slot); $\overline{E}_{t2}$ for transmitting data per time unit; $\overline{E}_c$ for a collision that lasts for one time unit; and $\overline{E}_i$ for an idle that lasts for one time unit. Note that $\overline{E}_{r2}$ and $\overline{E}_{t2}$ can be computed similarly to $\overline{E}_{r1}$ and $\overline{E}_{t1}$, respectively; while $\overline{E}_c$ and $\overline{E}_i$ are obtained by measurements as E_{elec}. Then, we can choose

$$e_2 = [w_s(\overline{E}_{r2} + \overline{E}_{t2}) + w_i\overline{E}_i + w_c\overline{E}_c]/\overline{D}_2, \tag{27}$$

where we choose $H_2 = \overline{D}_2$ for our network model, in which most CMs communicate to their CHs directly because they are within one hop distance of their CHs. Note that D_2 is averaged over all the CMs within a cluster, while $\overline{D}_2$ is further averaged over time, which can be calculated based on the average value of k by using Eqns. (18) and (11).

D. Measurement-Based Dynamic Clustering

1) Estimation of the Number of Active Nodes: In the previous section, the dynamic clustering of a node is based on the measurement of the signal power received from the boundary of the node's radio range, which is sensitive to measurement errors. In this section, we develop a new algorithm to estimate n in terms of the total power a node has received from all the neighboring nodes within its radio range.

Let's denote Φ_t the total signal power a node has received from all the neighboring nodes within its radio range. In terms of $n = \lambda|A|$, we can see that a change in n is due to a change in λ. Let's denote variable intensity as λ_t. We have

$$\begin{aligned}\Phi_t &= \int_\Omega \lambda_t p_m S_r d\omega \\ &= \lambda_t \pi r_0^2 S_0 p_m + \int_0^{2\pi}\int_{r_0}^{r_a} \lambda_t p_m \frac{\epsilon_0}{r^\gamma} r d\theta dr \\ &= \lambda_t p_m \Phi_0,\end{aligned} \tag{28}$$

where

$$\Phi_0 = \begin{cases} \pi r_0^2 S_0 + 2\pi\epsilon_0 \frac{r_0^{1-\gamma} - r_a^{1-\gamma}}{\gamma - 1}, & \text{for } \gamma > 2; \\ \pi r_0^2 S_0 + 2\pi\epsilon_0 \ln(r_a/r_0), & \text{for } \gamma = 2; \end{cases} \tag{29}$$

and p_m is the probability that a sensor transmits a packet at the beginning of an empty slot in MAC layer, as we mentioned in choosing e_2. Thus,

$$\lambda_t = \frac{\Phi_t}{p_m \Phi_0}. \tag{30}$$

It can be seen that the intensity changes proportionally to the total power a node has received for a specific radio range. In this way, by measuring the total power, a node can find the total number of active nodes in the network:

$$n_t = \lambda_t |A| = \frac{|A|}{p_m \Phi_0}\Phi_t. \tag{31}$$

A CM that has not been selected as a CH during its previous round can also monitor the total signal power it has received. In the next round of cluster updating, the node can join the competition and may become a CH by wining the competition.

Assume that during the j-th cluster updating cycle, and the measurement of Φ_t is denoted as $\tilde{\Phi}_t(j)$. In terms of Eqn. (31), we can find

$$\tilde{n}(j) = \frac{|A|}{p_m \Phi_0}\tilde{\Phi}_t(j), \tag{32}$$

where $\tilde{n}(j)$ is the calculated value of n in the j-th cluster updating cycle. During the $(j+1)$-th cluster updating cycle, $\tilde{n}$ is used to obtain an estimation of n, which is denoted as $\hat{n}$. To obtain smooth estimations, we use a moving averaging model:

$$\hat{n}(j+1) = \beta\hat{n}(j) + (1-\beta)\tilde{n}(j+1), \tag{33}$$

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

By substituting the value of $\hat{n}$ for n in Eqn. (22), and defining a coefficient:

$$c_n = 1/(c_3^2\hat{n}), \tag{34}$$

then the cubic equation can be solved:

$$q = c_n/3 + \sqrt[3]{U + \sqrt{U^2 - V^3}} + \sqrt[3]{U - \sqrt{U^2 - V^3}}, \tag{35}$$

where

$$U = (2c_n^2 + 18c_n + 27)c_n/54, \tag{36}$$
$$V = (c_n + 6)c_n/9. \tag{37}$$

Note that $U^2 > V^3$, therefore, Eqn. (35) is the only real root of Eqn. (22).

Then, the values for k and r_a can be easily calculated in terms of Eqns. (2) and (11), respectively.

In summary, each node does not need to know the number of active nodes a prior, nor rely on counting broadcasted "hello" messages from other nodes. The parameters n and k are estimated in real-time by each node in a distributed way. It makes completely autonomous decision about whether to form or join a cluster.

2) The Dynamic Clustering Algorithm: After obtaining the values of n and q, the process of cluster formation, and thus updating, is the same as in LEACH by using advertisement and join-request messages. More details can be found in Section III-B in [3]. Here, we focus on the activation of the dynamic clustering process.

The dynamic clustering algorithm can be outlined as follows:

1. Specify the value of σ, such as $\sigma = 0.001$. The initial value $n(0)$ does not have to be given. Initially, each node can be assigned with an initial value $q(0)$, which can be computed for all the nodes for a chosen value $n(0)$. Set $j = 1$.

2. Each node measures the total signal power it has received from all the neighbors within its radio range.

3. Each node computes its estimation of the number of active nodes in the network by using Eqns. (32) and (33).

4. Each node can decide whether or not to activate an updating process by checking the inequality:

$$|\hat{n}(j) - \hat{n}(j-1)| \le \delta, \tag{38}$$

where δ is a predefined constant that determines the allowable changes in n. If Eqn. (38) holds, go to step 2, to monitor the network status. Otherwise, go to step 5.

5. If the time since last cluster updating is longer than a predefined constant, activate the cluster updating process.

6. Each node computes its optimal probability of becoming CH in terms of Eqn. (35). Each node adopts the optimal probability and tries to become a CH with this new probability.

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

In this algorithm, both the number of clusters and the CHs are adjusted dynamically. By dynamically choosing CHs among all the nodes in the network, the energy dissipation is evenly distributed among all these nodes, thus the network lifetime is prolonged. Note that the cluster updating is a distributed process. Each node makes completely autonomous decisions on the activation of the cluster updating. For example, if in an area of the network some nodes die out due to power exhaustion, the remaining nodes in the area will see the decrease in n and thus activate the cluster updating process. In order to maintain the same DOI, the remaining nodes increase their operational radio range and thus the number of clusters is reduced, i.e., some clusters in the area may be merged into a larger cluster.

IV. Multihop Routing

We assume that a node knows the power level used in transmitting a packet. The radio transceiver of the node is capable of estimating the received signal power level. We also assume that the node is powered by battery, for which the function that describes its lifetime is not known.

A. Routing Metrics

To be energy-efficient, the routing protocol needs to consider the energy consumed in communications among the nodes that participate in the routing, which are CHs.

Let's denote E_{ij} the path loss for a wireless link l_{ij} that goes from node i to j, with a distance of d_{ij}. In terms of the propagation model in Eqn. (5), we can find

$$E_{ij} = \epsilon_1 / d_{ij}^{\gamma}, \tag{39}$$

where $\epsilon_1 = \kappa r_0^{\gamma}$. If i has the location information about j, the pass loss can be directly calculated in terms of Eqn. (39). Otherwise, we can either use localization schemes such as the positioning technique in [25], [26] to estimate the distance between i and j, or simply embed the value of i's transmitting power into the payload of a packet sent from i to j. The path loss is simply the difference between the transmitting power used by i and the signal power received by j.

Let's denote E_r the energy consumed in receiving the signal. The total amount of energy needed to be consumed in order to send a packet over the one-hop distance is:

$$E_i = E_{ij} + E_r. \tag{40}$$

Note that a source node only needs to transmit, while a destination node only needs to receive.

To be power-aware, the routing protocol needs to consider the battery power of the nodes that participate in the routing. Let's denote B_{0i} the new battery power of a node i. The accumulated power consumption of the node is denoted as B_{ci}, which can be recorded by the node itself. Thus, the remaining battery power of the node is $B_{0i} - B_{ci}$. To incorporate the remaining battery power into link cost, we define a dimensionless coefficient:

$$w_i = \frac{B_{ci}}{B_{0i} - B_{ci}}, \tag{41}$$

where it can be seen that less remaining battery results in a much bigger value for the coefficient.

To be both energy-efficient and power-aware, the routing protocol can use the following link cost function:

$$D_i = w_i E_i, \tag{42}$$

where w_i is used as a weighting factor for the link's energy consumption E_i; and D_i has the dimension of energy. A bigger value of D_i means a higher cost for the link to be selected, which is due to either the higher energy consumption of the link or the lower remaining battery power in the node, or both.

Consider a path $p \in P_{sn \to bs}$, where $P_{sn \to bs}$ is the set of paths that go from a source node sn to a destination bs, i.e., $P_{sn \to bs} = \{\text{all the paths from } sn \text{ to } bs\}$. The cost for the path is:

$$D(p) = \sum_{i \in p} w_i E_i, \quad p \in P_{sn \to bs}. \tag{43}$$

Note that the cost is additive. Suppose that a link l_{ij} is on the path, i.e., $l_{ij} \in p$. Let's denote p_i the path from sn to i and p_j the path from sn to j. Then, we have

$$D(p_j) = D(p_i) + \frac{B_{cj}}{B_{0j} - B_{cj}} E_j, \quad \text{for } l_{ij} \in p. \tag{44}$$

Now the optimal routing problem can be stated as:

$$\min_p \sum D(p), \quad p \in P_{sn \to bs}, \tag{45}$$

and subject to the constraints:

$$B_{0i} - B_{ci} \geq B_{ref}(t) \geq B_{min}, \quad i \in p, \tag{46}$$

where $B_{ref}(t)$ is a reference value for the remaining battery power that is required by the base station for any node to be allowed to join current route selection; B_{min} is the minimum battery power required for a node to be considered as active.

Many algorithms in distributed routing can be used to find a global optimal solution to Eqns. (45) and (46), e. g., the Dijkstra algorithm and the distributed asynchronous Bellman-Ford algorithm [12]. To find a global optimal solution by solving the Eqns. (45) and (46), a source node, which can be possibly any one of the CHs, needs to communicate to all other CHs and conduct intensive computations.

B. Routing Algorithm

We develop a routing algorithm to avoid the intensive computations and communications in order for a sensor node to make its optimal routing decisions.

The heuristic algorithm can be summarized as follows.

1. During the topology discovery phase, a source node sends out a route request packet, which is flooded to the BS. Each node along a path also embeds its transmitting power and the cost of the path from the source into the packet sent to its

next hop. The receiving node then updates its cost in terms of Eqn. (44).

2. Upon receiving multiple copies of the route request packet, the BS computes a total cost for each of the paths originated from the source node. It then selects multiple routes as candidates and sends back a route reply message over the candidates. The message contains the total cost of the path and a reference value $B_{ref}(t)$. If the current battery power of a node does not meet Eqn. (46), the node will not be allowed to join the current routing and the candidacy of its route is removed.

3. Upon receiving the multiple copies of the route reply message, the source finds out a few routes to reach the BS and the associated cost for each route. Therefore, the source is able to choose the one with minimum cost and confirm the route, which is both energy-efficient and power-aware, if it exists. If none of the candidates meet the battery requirement, then the BS is informed to lower the value of $B_{ref}(t)$ and the procedure repeats.

4. Once the route is established, the source starts to send data to the BS.

Remarks on the algorithm:

- By using the reference, the selected routes are more evenly distributed over the entire the network so that the network lifetime can be prolonged.
- The BS does not choose a final route because it does not know the battery status of the nodes.
- The value of $B_{ref}(t)$ can be chosen by the BS in terms of the estimation of the average power consumption per node at the current time, which can be computed based on the observed total energy consumption of the network. The BS is assumed to have enough computation capability and power to accumulate all the energy consumption information within the network.

Note that the above procedures cannot be carried out by simply flooding the route request packet because the nodes do not know the current reference, unless the BS periodically floods the reference value, which costs more energies.

The proposed routing algorithm has been simulated by using NS-2, with route discovery and path setup procedures modified from AODV.

V. Simulation Studies

The network architecture is shown in Fig. 1. The parameters are the same as in [2], $a = 50m$, and $\sigma = 0.001$, except that the BS is at the middle of the right side of the area. The radio propagation model is Eqn. (6), with coefficient $\epsilon_0 = 1$, for simplicity. The intensity of the spatial Poisson process is $\lambda = n/|A|$, where $n = 100 \sim 2500$.

The simulations have two parts and are conducted to verify the proposed dynamic clustering and routing algorithms, respectively. The first part uses MATLAB version 6.5 while the second uses NS-2 simulator [27].

A. Simulations on Dynamic Clustering

To verify the correctness of the proposed real-time estimation algorithm, we assume that the measurement error can be described by a white Gaussian noise. Initially, each sensor randomly selects its q value and tries to become a CH if $q > q_0$, where q_0 is an initial value for q. For example, we choose $q_0 = 0.1$. During a clustering cycle, each sensor collects the minimum signal power it has received so far within its radio range. By using Eqn. (24) to estimate the $\hat{k}$ value, and then using Eqn. (23) to compute the q value, each sensor can estimate the $\hat{n}$ value in terms of Eqn. (25). The procedure repeats until it sees no obvious change in its estimated $\hat{n}$ value.

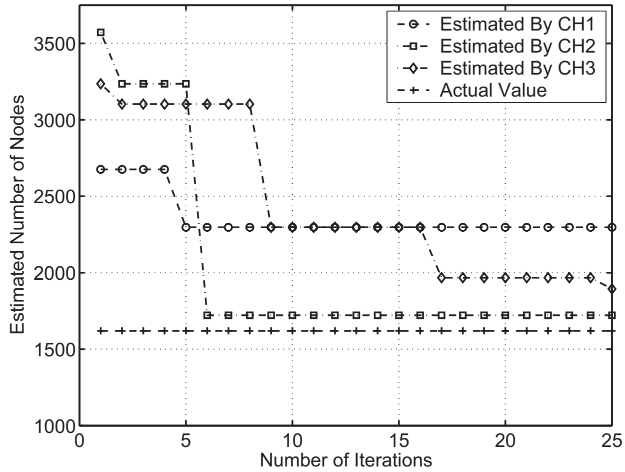

Fig. 3. Estimating the number of active nodes (n) by using the minimum signal power (S_a) that has been received by a CH within its cluster (for $n = 1600$).

As an example, for $n = 1600$, the actual and estimated n values are shown in Fig. 3 for three CHs. It can be seen that the estimated value is getting closer to the actual value as the measured signal power is getting smaller. Although CH2 finds the $\hat{n}$ value at the 6-th iteration with an error about 10%, CH1 and CH3 do not find the right value up to 25 iterations. Clearly, missing any one signal power measurement that is smaller than its existing one results in a large error on the $\hat{n}$ value.

In contrast, each sensor collects the total signal power it has received within its radio range and then estimates the value of n by using Eqns. (32) and (33). The result is shown is shown in Fig. 4 for a CH. It can be seen that the smoothed estimation of n gets close to the actual value within about 5 iterations, although an individual estimation may have large error. Clearly, missing any single measurement of the signal power has no significant impact on the estimation of n value. Therefore, the real-time estimation algorithm outperforms the existing ones [19], [20].

Based on the estimated $\hat{n}$ value, each sensor node computes its optimal probability of becoming CH in terms of Eqn. (35). As an example, by applying the proposed dynamic clustering algorithm, a clustered network of $n = 200$ is shown in Fig. 5.

To verify the energy efficiency of the dynamic clustering technique, and also compare it to LEACH and HEED, the values for the energy related parameters are the same as in [3], [10], as shown in Table I. The network is shown in Fig. 2, in which $a = 50m$ and the BS is $75m$ to the middle of the right side of the network. The energy consumption per bit for transmission and receiving are $E_{elec} + \epsilon \times d^{\gamma}$ and E_{elec}, respectively; where γ and ϵ take different values depending

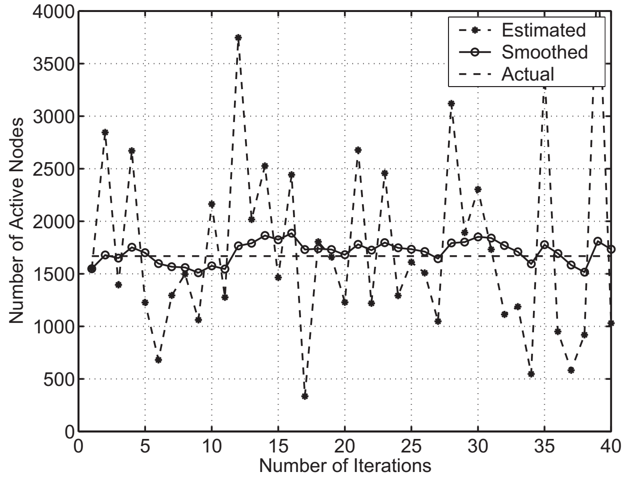

Fig. 4. Estimating the number of active nodes (n) by using the total signal power (Φ_t) that has been received by a CH within its cluster (for $n = 1600$).

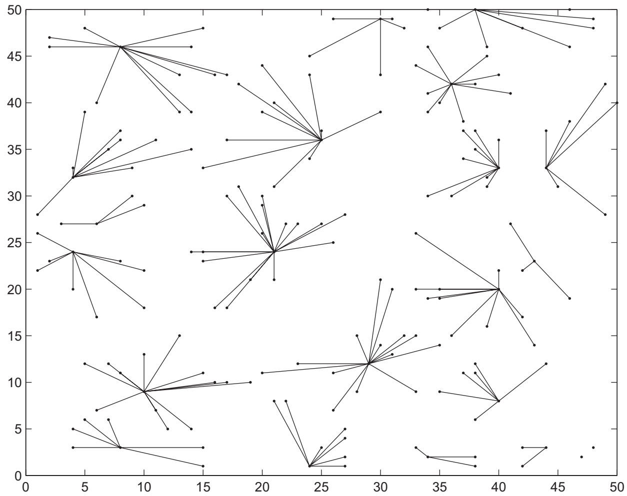

Fig. 5. The simulated scenario of a clustered network ($n = 200$).

on d. For a CH, the energy spent in aggregating the data from its CMs is E_{fusion}, as defined in [3].

The energy efficiency of clustering is measured by the ratio of the energy spent in clustering to the total energy spent in both clustering and one-hop transmission, where it is assumed that the CHs can directly communicate to the BS for the purpose of comparison. The ratios for different clustering methods are plotted in Fig. 6, where the results for LEACH and HEED are extended from $n = 300 \sim 700$ to $n = 100 \sim 2500$ for comparison. It can be seen that the proposed dynamic clustering method (labeled as EEDC in the figure) is the most efficient for large-scale sensor network. For example, for $n = 2000$, EEDC consumes only half of the energy as HEED and only one third of energy as LEACH. The reason is that the energy efficiency is roughly proportional to m/k. As n increases, m/k increases accordingly if k is fixed, as in current static clustering. With EEDC, the optimal k increases faster than m. Thus, m/k decreases as n increases. Note that HEED chose an initial q value that was very close to the optimal q value, although the energy efficiency was not optimized in HEED, as the authors pointed out.

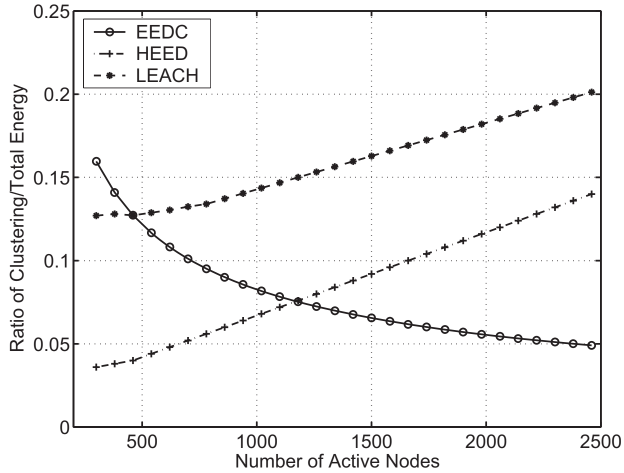

Fig. 6. The ratio of the clustering energy to the total dissipated energy.

B. Simulations on EEPA Routing

The tier-two network is assumed to have an area of $100m \times 100m$, as shown in Fig. 1. The number of nodes (CHs) is $10 \sim 50$, which corresponds to $n = 200 \sim 2500$ without clustering. The radio range is $25m$. The other parameters are defined in Table I, except the initial battery power $E_{battery} = 50J$ per battery, and the transition time = $0.005s$. The total simulation time is $20000s$.

We define the lifetime of the network is the time until the first node dies out due to its energy depletion, denoted as T_{1st} [18]. The lifetime of a specific method is denoted by a superscript, for example, T_{1st}^{AODV} and T_{1st}^{EEPA} are the lifetime achieved by AODV and EEPA, respectively. Similarly, the lifetime can be also defined as the time when 50% of nodes die out, denoted as T_{50p}.

To compare the lifetime of the proposed EEPA routing to that of AODV, we define a relative increase in the lifetime as

$$\Delta T_{1st} = (T_{1st}^{EEPA} - T_{1st}^{AODV})/T_{1st}^{AODV}, \quad (47)$$
$$\Delta T_{50p} = (T_{50p}^{EEPA} - T_{50p}^{AODV})/T_{50p}^{AODV}. \quad (48)$$

Similarly, we can define the increase in the lifetime as compared to MTE and MRE.

Compared to AODV, the simulation results are plotted in Fig. 7. It can be seen that the increase in T_{1st} is about $13 \sim 22\%$ for a tier-two network of size $10 \sim 50$. The increase in T_{50p} is about $22 \sim 32\%$, which is significantly high as it means that the network would operate about $45 \sim 60\%$ more time if the lifetime of all the nodes is considered. The total energy consumption is reduced by half. As the number of nodes increases, the increase in the lifetime is more significant.

Compared to MTE, EEPA increases T_{1st} and T_{50p} by percentages up to 16% and 23%, respectively, as shown in Fig. 8. Also plotted in Fig. 8 is the comparison of EEPA to MRE in network lifetime. Clearly, EEPA consistently outperforms both MTE and MRE in network lifetime because it considers both requirements of energy-efficiency and power-awareness.

It is worth pointing out that the gain in lifetime is achieved by the increase in the routing overhead, which is defined as the number of data packets delivered by per routing packet. For the network sizes of $n = 25$ and 50, the overheads of EEPA

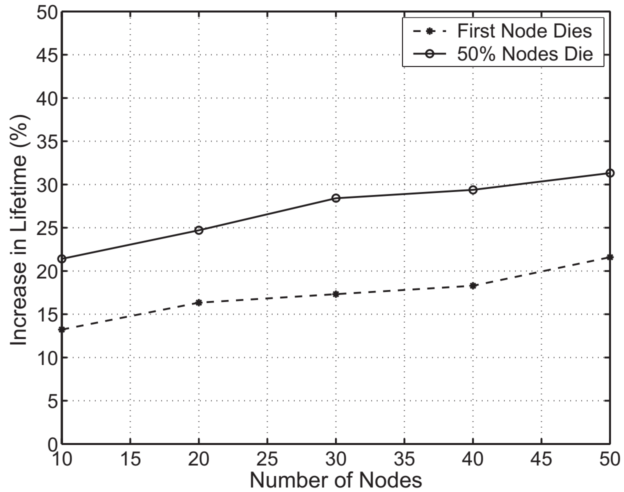

Fig. 7. The increase in the network lifetime by using EEPA as compared to AODV.

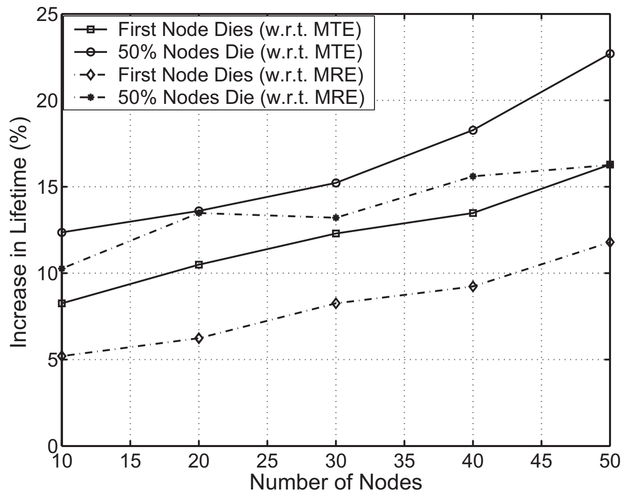

Fig. 8. The increase in the network lifetime by using EEPA as compared to MTE and MRE.

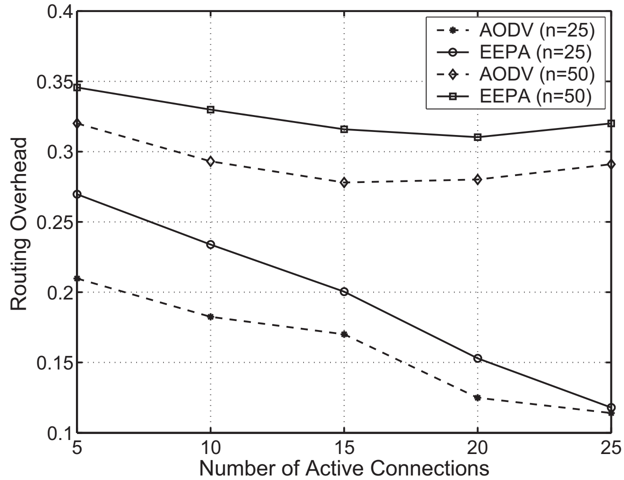

Fig. 9. The routing overhead for EEPA and AODV.

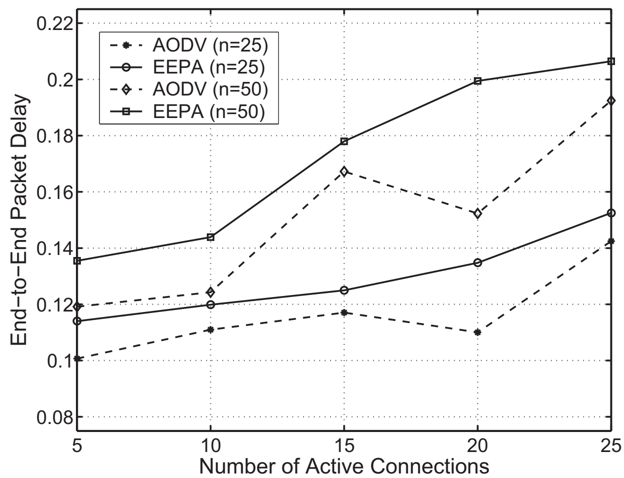

Fig. 10. The end-to-end packet delay for EEPA and AODV.

and AODV are plotted in Fig. 9, respectively. The overhead of EEPA is higher than that of AODV because EEPA waits for multiple requests (or replies) at the destination (or source) in order to choose an EEPA route. Note that if we define the overhead as per bit of data delivered by per bit of routing information, then the routing overhead would be much lower. Because in our simulations, the size of the data packets is 512 bytes while the size of control packets is only 44 bytes. It can be also seen in the figure that the difference in the overhead between AODV and EEPA decreases as the number of connections increases. The reason is that AODV has to perform more frequent route discovery due to the death of nodes as compared to EEPA.

To investigate the performance of EEPA, we measure the end-to-end delay in the simulations. The results are shown in Fig. 10. As can be seen that the end-to-end delay curve for EEPA is very close and similar to the one for AODV, which is a minimum hopcount routing that ideally should have the shortest delay. In fact as the number of nodes increases, EEPA tries to emulate AODV and uses shortest paths because there are more choices among the nodes that have high residual energy. It toggles between nodes with higher residual energy so as not to drain the nodes as in AODV. This is also verified by the average hopcount for different numbers of nodes, as shown in Fig. 11. It can be seen that EEPA has higher than but very close to the hopcount of AODV. As compared to AODV, EEPA favors paths with less path loss and thereby slightly increases the hopcount to ensure the required energy-efficiency.

VI. Conclusion

In this paper, we develop a dynamic clustering technique for large-scale sensor networks. Based on the clustered network architecture, we also propose an energy-efficient and power-aware routing algorithm for the tier-two network that consists of the cluster heads. The simulation results have demonstrated that the proposed clustering technique and routing algorithms adapt to changes in node power levels, scale well to large-scale networks, and are energy-efficient.

Our future work would be further investigating the applicability of the proposed clustering technique and routing algorithm to more general wireless sensor networks.

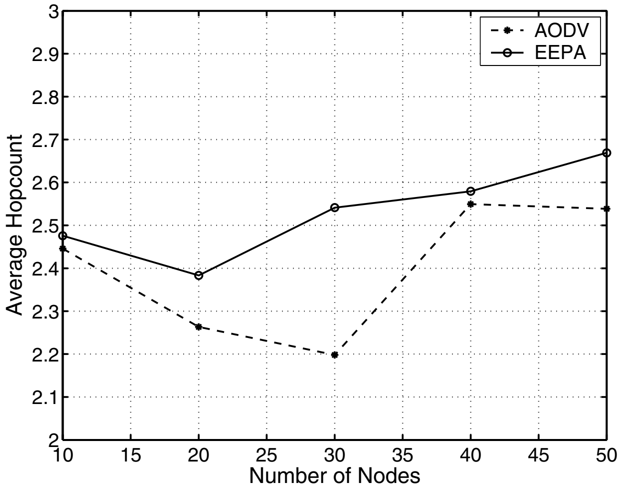

Fig. 11. The average hopcount for EEPA and AODV.

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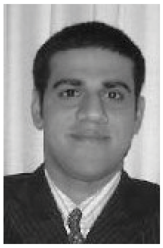

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