ERAS: Energy-Efficient Routing Strategy with Adaptive Cluster-Head Selection in WSNs

You-Chiun Wang and Pei-Yu Lin
Department of Computer Science and Engineering,
National Sun Yat-sen University, Kaohsiung, 80424, Taiwan
Email: ycwang@cse.nsysu.edu.tw; peggy12423@gmail.com

***Abstract*—In a *wireless sensor network (WSN)*, sensors close to the sink deplete energy quickly as they relay a large amount of data, causing the energy hole problem. Cluster-based routing is a common solution that groups sensors into clusters and then selects *cluster heads (CHs)* to route packets. Many cluster-based routing methods consider that sensors are evenly deployed in the sensing field. However, the distribution of sensors may be non-uniform. Some clusters would include many sensors, imposing their CHs with heavy loads and raising packet loss due to buffer overflow. This paper proposes an *energy-efficient routing with adaptive CH selection (ERAS)* strategy, which divides the sensing field into grids and decides the last grid to the sink. For grids with more sensors, multiple CHs are chosen to share the routing work. The selection of CHs considers sensors' distribution and remaining energy. Based on the energy status, sensors take turns to serve as CHs to balance their energy consumption. Simulation results reveal that the ERAS strategy can efficiently raise WSN lifetime and diminish packet loss.**

***Index Terms*—cluster, energy, route, wireless sensor network.**

I. Introduction

Wireless sensor networks (WSNs) are frequently employed to better our lives as a result of the IoT's growing popularity [1]. A WSN is made up of numerous small sensors deployed in a sensing field to gather information about the environment and send it to a sink. Practical applications for WSNs include, for instance, air-quality monitoring [2], border surveillance [3], elder care [4], precision farming [5], smart shopping [6], building evaluation [7], and pollution tracing [8].

Sensors are powered by tiny batteries, but replacing batteries is usually not cost-effective. As a result, how to conserve sensors' energy is crucial to extending a WSN's lifetime. In general, communication has a major influence on how much energy sensors spend [9]. To convey data to the sink, sensors in a large WSN typically rely on multihop communication. Most sensors need to relay packets from their upstream nodes further away from the sink. Those sensors near the sink would inevitably consume energy more quickly, thereby putting the WSN at risk of network partition. The above issue is referred to as the *energy hole problem* [10].

Cluster-based routing is a prevalent solution to this problem [11]. Sensors are grouped into clusters such that nearby sensors belong to the same cluster. In each cluster, a *cluster head (CH)* takes charge of the routing work, where it receives data from other sensors and sends data to the sink. Cluster-based routing has two benefits. First, since only CHs partake in routing, other sensors can conserve energy (as they do not need to relay data from others). Second, CHs can employ a compression approach to integrate and condense the received data, which helps cut down the quantity of data sent to the sink and thus reduce energy consumption [12].

TABLE I: Summary of acronyms.

acronym	full name
ARE	anticipated residual energy
CH	cluster head
ERAS	energy-efficient routing with adaptive CH selection
E-DSR	energy-efficient routing for sensors with diverse sensing rates
NRCA	node ranking clustering algorithm
O-LEACH	optimization of LEACH
PLR	packet loss rate
TEE	total expected energy
WSN	wireless sensor network

How to efficiently select CHs is an important issue. Many cluster-based routing methods assume that sensors are evenly distributed in the sensing field, and select CHs based on their energy or proximity to the sink. In effect, the distribution of sensors can be random and non-uniform [13]. Some clusters may include many sensors, which not only burdens their CHs with heavy loads but also increases packet loss due to buffer overflow at these CHs. Even worse, after selecting sensors to be CHs, some methods ask them to serve as CHs for a long time. Doing so hastens their energy depletion.

This paper proposes an *energy-efficient routing with adaptive CH selection (ERAS)* strategy, which uses a grid structure in the sensing field and decides the last grid to reach the sink. Instead of choosing one CH for each grid, we adaptively pick more CHs in grids with more sensors for load-sharing consideration. The selection of CHs is based on the distribution of sensors and their residual energy. CH reselection is performed by referring to the CH's energy status to avoid some sensors consuming much energy owing to serving as CHs for a long time. Our contribution is to design an energy-efficient cluster-based routing strategy for WSNs whose sensor distributions can be non-uniform. Simulation results demonstrate that the ERAS strategy can significantly improve WSN lifetime while reducing the *packet loss rate (PLR)* as compared with other cluster-based routing methods.

The rest of this paper is organized as follows: Section II surveys related work, and Section III gives the system model. We detail our ERAS strategy in Section IV and evaluate performance in Section V. Then, Section VI draws a conclusion. Tables I and II summarize acronyms and notations.

II. Related Work

Compared to flat routing, which lets each sensor take part in routing packets, cluster-based routing has the superiority

TABLE II: Summary of notations.

notation	definition
$\hat{\mathcal{G}}$	set of grids whose sensors can directly communicate with the sink
N_k	number of sensors in a grid G_k
C_k	number of CHs allocated to G_k, $C_k \in [C_{\min}, C_{\max}]$
$\mu^{\mathbf{N}}$, $\sigma^{\mathbf{N}}$	mean and standard deviation of the number of sensors in each grid
e_i	residual energy of a sensor s_i
$\mu_k^{\mathbf{E}}$, $\sigma_k^{\mathbf{E}}$	mean and standard deviation of residual energy of all sensors in G_k
$\Gamma_{\mathbf{G}}(s_i, \lambda)$	energy for s_i to generate a packet with λ-bits
$\Gamma_{\mathbf{S}}(s_i, s_j, \lambda)$	energy for s_i to send a packet with λ-bits to node s_j
$\Gamma_{\mathbf{R}}(s_j, \lambda)$	energy for s_j to receive a packet with λ-bits
$\lambda_{\mathbf{U}}$, $\lambda_{\mathbf{C}}$	lengths of uncompressed and compressed packets

of extending WSN lifetime [14]. LEACH is a representative of cluster-based routing [15], where each sensor determines a probability p_i. If p_i exceeds threshold ϱ, the sensor becomes a CH, and nearby sensors join its cluster. There are numerous variations of LEACH. Salim et al. [16] consider decreasing a LEACH CH's load through sharing its routing work with other sensors. In [17], except for the CH, a sensor possessing the most energy serves as a vice CH for fault tolerance. Tang et al. [18] use an energy potential function to decide threshold ϱ, which considers both the mean and variance of sensors' energy. The work [19] applies fuzzy logic to improve LEACH performance. Salman et al. [20] propose an *optimization of LEACH (O-LEACH)*, which picks CHs based on their residual energy and distances to the sink. However, LEACH and its variations make CHs directly transmit data to the sink, which may deplete their energy quickly.

A few studies organize WSNs into special structures. Both [21] and [22] consider a ring-based topology, where the sink is located at the ring's center. They take account of the ring number when selecting CHs. Chen et al. [23] group sensors into clusters and use an ant-colony optimization algorithm to form chains in clusters. The work [24] builds a cluster tree to collect data based on a bio-inspired method. Evidently, these studies consider different network structures from ours.

Several studies divide a sensing field into grids. The *node ranking clustering algorithm (NRCA)* [25] picks a sensor with the most energy as the CH in each grid. If events occur, the work [26] allows sensors to send data to CHs in nearby grids to facilitate data compression. In [27], some CHs may sleep to conserve energy, so not all CHs participate in routing. The *energy-efficient routing for sensors with diverse sensing rates (E-DSR)* method [28] splits or merges grids to mitigate buffer overflow or improve data compression at CHs. Nevertheless, the above methods assume that sensors are evenly deployed and select one CH in each grid. This motivates us to propose the ERAS scheme that considers non-uniform distribution of sensors and uses multiple CHs for load sharing.

III. System Model

We are given a sensing field on which sensors are deployed (may not necessarily be uniformly distributed) for collecting and reporting data to a sink. Sensors are static and homogeneous, meaning that they have the identical hardware, battery capacity, communication range, and buffer size. If one sensor has a full buffer, but new packets come (e.g., produced by or sent to the sensor), they are dropped due to buffer overflow.

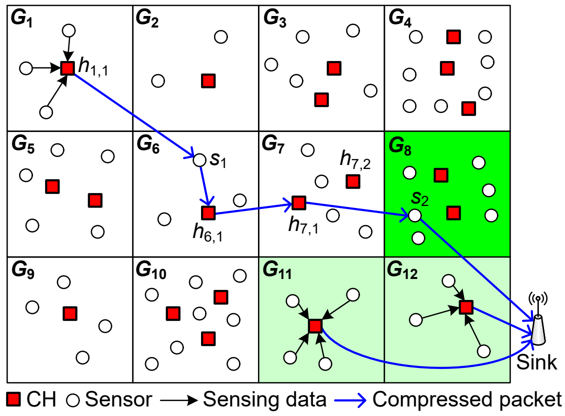

Fig. 1: Grid management and packet forwarding in ERAS.

The sensing field is divided into grids. Sensors' positions are known using some localization methods [29]. CHs can adopt a data compression algorithm to condense packets received from other sensors and send compressed packets. However, compressed packets cannot be further condensed.

Regarding the energy consumption model, we consider the amount of energy for sensors to spend on generating, sending, and receiving data [30]. Suppose that a sensor s_i generates one packet of sensing data whose length is λ bits. Then, s_i uses an amount of energy by $\Gamma_{\mathbf{G}}(s_i, \lambda) = \left(v_i^{\mathbf{G}} \times c_i^{\mathbf{G}} \times t_i^{\mathbf{G}}\right) \times \lambda$, where $v_i^{\mathbf{G}}$, $c_i^{\mathbf{G}}$, and $t_i^{\mathbf{G}}$ respectively represent the voltage, current, and time required by s_i to create the packet. When s_i forwards the packet to another node s_j (i.e., a sensor or the sink), s_i consumes an amount of energy by $\Gamma_{\mathbf{S}}(s_i, s_j, \lambda) = (\alpha_i^{\mathbf{T}} + \alpha_i^{\mathbf{A}} \times \tilde{D}(s_i, s_j)^2) \times \lambda$. Here, $\alpha_i^{\mathbf{T}}$ and $\alpha_i^{\mathbf{A}}$ signify the power for s_i's transmitter and amplifier circuits used to send a bit, and $\tilde{D}(s_i, s_j)$ gives the distance between s_i and s_j. On the other hand, the amount of energy taken by s_j to receive the packet is $\Gamma_{\mathbf{R}}(s_j, \lambda) = \alpha_j^{\mathbf{R}} \times \lambda$, where $\alpha_j^{\mathbf{R}}$ is the power for s_j's receiver circuit to acquire one single bit.

Our objective is to choose CHs and find routing paths to the sink to maximize WSN lifetime and minimize PLR. WSN lifetime can be defined by the amount of time since the WSN begins to operate until the first sensor uses up energy. PLR is calculated by the number of packets successfully sent to the sink divided by the number of packets generated by sensors. Since data compression is adopted in CHs and the sink has to decompress the received packets, we account for the number of uncompressed packets at the sink's side in the numerator.

IV. The Proposed ERAS Strategy

ERAS contains four modules. The *grid management module* decides the number of CHs in each grid and which grid is the last to reach the sink. The *CH selection module* picks out CHs in each grid. Then, the *packet forwarding module* deals with how to send packets to the sink. To prevent CHs from rapidly depleting energy, the *CH alternation module* makes sensors in a grid serve as CHs by turns.

A. Grid Management Module

As discussed in Section II, existing solutions select one CH in each grid. Actually, we shall pick more CHs for grids with many sensors to share loads. Suppose that a grid G_k has N_k sensors. Let $\mu^{\mathbf{N}}$ and $\sigma^{\mathbf{N}}$ be the mean and standard deviation

Algorithm 1: K-means Scheme

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Pick C_k sensors as the initial center of each group;
repeat
    Assign each sensor in G_k to a group whose
      distance to the group's center is the closest;
    Recompute each group's center;
until sensors in each group do not change;
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of the number of sensors in each grid. Then, we compute the number of CHs for G_k (denoted by C_k) as follows:

$$C_k = \begin{cases} C_{\min} & \text{if } N_k \leq \mu^{\mathbf{N}} \\ \min\{C_{\min} + \zeta, C_{\max}\} & \text{otherwise,} \end{cases} \tag{1}$$

where $C_{\min}, C_{\max}, \zeta \in \mathbb{Z}^+$ and $C_{\min} < C_{\max}$. Moreover, we have $\mu^{\mathbf{N}} + (\zeta - 1) \times \sigma^{\mathbf{N}} < N_k \leq \mu^{\mathbf{N}} + \zeta \times \sigma^{\mathbf{N}}$ if $N_k > \mu^{\mathbf{N}}$. The meaning behind Eq. (1) is as follows: If the number of sensors in G_k does not overtake the average of all grids (i.e., $\mu^{\mathbf{N}}$), G_k is allocated the minimum number of CHs (i.e., $C_{\min}$). Otherwise, G_k has more sensors. Based on the multiple of the standard deviation (i.e., $\zeta \times \sigma^{\mathbf{N}}$) that N_k is over the mean $\mu^{\mathbf{N}}$, we increase the number of G_k's CHs accordingly. However, each grid can be allocated at most $C_{\max}$ CHs. Fig. 1 presents an example, where $C_{\min} = 1$ and $C_{\max} = 3$.

Traditionally, grid G_a next to the sink is viewed as the *last grid* (e.g., G_{12} in Fig. 1), where the last hop of each routing path to reach the sink takes place. When the distribution of sensors is not evenly, G_a may have relatively fewer sensors, thereby worsening the energy hole problem. Hence, we check if there is another grid with better conditions that can replace G_a as the last grid. Let $\hat{\mathcal{G}}$ be the set of grids whose sensors are capable of directly communicating with the sink. For each grid G_k in $\hat{\mathcal{G}}$, we estimate the amount of *total expected energy (TEE)* as follows:

$$\text{TEE}_k = \sum\nolimits_{s_i \text{ in } G_k} e_i - \varepsilon \times \Gamma_{\mathbf{S}}(\phi_k, \text{sink}, \lambda_{\mathbf{C}}), \tag{2}$$

where e_i gives the residual energy of a sensor s_i, ϕ_k denotes G_k's center, and $\lambda_{\mathbf{C}}$ is the length of a compressed packet. In Eq. (2), $\sum_{s_i \text{ in } G_k} e_i$ is the amount of energy of all sensors in G_k, and $\varepsilon \times \Gamma_{\mathbf{S}}(\phi_k, \text{sink}, \lambda_{\mathbf{C}})$ predicts the amount of energy for these sensors to relay ε compressed packets from other grids (e.g., $\varepsilon = 1000$). As discussed later in Section IV-C, all sensors in the last grid have the opportunity to participate in the last hop. To simplify the calculation in TEE, we take ϕ_k on behalf of G_k's sensors for packet relay. If a grid has a larger TEE, it implicitly means that the grid has more sensors, these sensors possess more residual energy, or they can spend less energy to send packets to the sink. Naturally, we select the grid with the largest TEE from $\hat{\mathcal{G}}$ as the last grid. Fig. 1 gives an example, where $\hat{\mathcal{G}} = \{G_8, G_{11}, G_{12}\}$, and we pick G_8 to be the last grid.

B. CH Selection Module

As mentioned in Section IV-A, a grid G_k is allocated C_k CHs. If $C_k > 1$, based on the distribution of sensors in G_k, we group them into C_k clusters using the K-means scheme. Algorithm 1 shows the pseudocode. However, the number of sensors in each cluster could vary significantly [31], making the routing burden unbalanced. Thus, we do an enhancement as follows: Let N_k be the number of sensors in G_k. Suppose that a cluster $\hat{\mathcal{Q}}_j$ has fewer than $\lfloor N_k/C_k \rfloor$ sensors. We pick a sensor s_i from another cluster with the most sensors, such that s_i is the closest to $\hat{\mathcal{Q}}_j$. Then, s_i is moved from its cluster to $\hat{\mathcal{Q}}_j$. This iteration is repeated until $\hat{\mathcal{Q}}_j$ contains $\lfloor N_k/C_k \rfloor$ sensors. Doing so ensures that the number of each cluster in G_k can be as close as possible.

Let us analyze the time complexity of this enhancement. Given N_k sensors in grid G_k, K-means takes $O(N_k^2)$ time to group them [32]. Since there are C_k groups in G_k and each group contains at least one sensor, no more than $(N_k - C_k)$ sensors will be moved between different groups. Hence, the time complexity is $O(N_k^2) + O(N_k - C_k) = O(N_k^2)$.

For each cluster $\hat{\mathcal{Q}}_j$ in G_k, we find a CH to take charge of $\hat{\mathcal{Q}}_j$'s routing work. In particular, we compute the *anticipated residual energy (ARE)* of each sensor $s_i \in \hat{\mathcal{Q}}_j$ by

$$\begin{aligned} \text{ARE}_i = e_i &- x_1 \times \Gamma_{\mathbf{G}}(s_i, \lambda_{\mathbf{U}}) - x_2 \times \Gamma_{\mathbf{R}}(s_i, \lambda_{\mathbf{U}}) \\ &- x_3 \times \Gamma_{\mathbf{S}}(s_i, s_y, \lambda_{\mathbf{C}}), \end{aligned} \tag{3}$$

where $\lambda_{\mathbf{U}}$ is the length of an uncompressed packet. Here, s_i's ARE will be equal to its current energy (i.e., e_i) deducted from the amount of energy for s_i to generate x_1 packets, to receive x_2 packets from other sensors in $\hat{\mathcal{Q}}_j$, and to send x_3 compressed packets to the next node (i.e., s_y, where we will discuss how to find this node in Section IV-C). Given a period of time T (in seconds, e.g., $T = 300\,\text{s}$), we can derive that 1) $x_1 = \lfloor r_i T \rfloor$, where r_i denotes s_i's *sensing rate*, as defined by the reciprocal of the interval between two successive packets of sensing data produced by s_i; 2) $x_2 = (|\hat{\mathcal{Q}}_j| - 1) \times \lfloor \mu_j^{\mathbf{R}} T \rfloor$, where $\mu_j^{\mathbf{R}}$ is the average sensing rate of sensors in $\hat{\mathcal{Q}}_j$; and 3) $x_3 = \lceil x_2/\vartheta \rceil$, where ϑ is the maximum number of packets that can be condensed in a single compressed packet. Then, the sensor with the maximum ARE value acts as $\hat{\mathcal{Q}}_j$'s CH.

C. Packet Forwarding Module

The packet forwarding module is composed of two parts: *intra-grid* and *inter-grid*. For the intra-grid part, each sensor sends packets to its CH in a grid via one-hop communication. On the other hand, after receiving a predefined number of packets (according to the data compression method), the CH combines and condenses them into a compressed packet.

The inter-grid part deals with how compressed packets are sent from each CH to the sink. There are two cases:

Case 1: Grids in $\hat{\mathcal{G}}$. Sensors in these grids can directly communicate with the sink. To reduce the burden of relaying packets in the last grid, CHs thus send compressed packets to the sink by employing one-hop communication. Let us take Fig. 1 as an example. CHs in grids G_8, G_{11}, and G_{12} straight send their compressed packets to the sink.

Case 2: Grids not in $\hat{\mathcal{G}}$. CH picks an adjacent grid nearest to the sink. As it does not know who acts as a CH in that grid, the CH sends compressed packets to a sensor s_i closest to it. If s_i is not a CH, s_i forwards compressed packets to its CH. Notice that these compressed packets will not be compressed again. One exception occurs in the last grid. Specifically, if a sensor in the last grid gets compressed packets from other grids, the sensor directly forwards them to the sink (instead of relaying them to its CH). Doing so helps reduce the burden

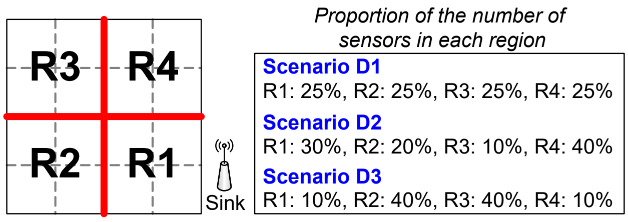


Fig. 2: Four regions of the sensing field.

on CHs in the last grid. Fig. 1 demonstrates an example. For a CH $h_{1,1}$ in G_1, the routing path for sending its compressed packets is $h_{1,1} \rightarrow s_1$ (a sensor in G_6) $\rightarrow h_{6,1}$ (s_1's CH) $\rightarrow h_{7,1}$ (a CH in G_7) $\rightarrow s_2$ (a sensor in the last grid) $\rightarrow$ sink.

D. CH Alternation Module

Since CH takes on most of the routing work, they consume energy faster than others. To balance the energy consumption of sensors in a grid, the CH alternation module gives them the opportunity to take turns serving as CHs.

Suppose that a sensor s_i has consumed a certain proportion of energy while serving as a CH for grid G_k in this round (for example, 1% of its energy). Then, s_i computes the z-score in terms of residual energy by $z_i = (e_i - \mu_k^{\mathbf{E}})/\sigma_k^{\mathbf{E}}$, where $\mu_k^{\mathbf{E}}$ and $\sigma_k^{\mathbf{E}}$ are the mean and standard deviation of residual energy of sensors in G_k. If $z_i \geq 0.253$, it implies that s_i's energy falls within the first 40% of all sensors in G_k. Hence, s_i can still act as a CH since s_i has relatively sufficient energy compared with most sensors in G_k. Otherwise, the reselection of CH is necessary. As a result, we employ the CH selection module in Section IV-B to pick out a new CH to replace s_i.

V. Performance Evaluation

In simulations, we consider a 400 m × 400 m sensing field, which is divided into 4×4 grids, as shown in Fig. 2. To study the effect of the number of sensors on system performance, we deploy 400, 500, 600, 700, 800, 900, and 1000 sensors on the sensing field. Each sensor has the communication range of 80 m, buffer size of 600 packets, and battery capacity of 6480 J. The sensing rate of each sensor is randomly picked from $\{1/90, 1/120, 1/150\}$. In other words, the sensor may generate one packet of sensing data every 90 s, 120 s, or 150 s. The packet length of sensing data is 200 bytes. Moreover, the relevant parameter settings for the energy consumption model discussed in Section III are listed as follows:

- **Data generating:** $v_i^{\mathbf{G}} = 1.5\,\text{V}$, $c_i^{\mathbf{G}} = 25\,\text{mA}$, and $t_i^{\mathbf{G}} = 0.25\,\text{ms}$ in $\Gamma_{\mathbf{G}}(s_i, \lambda)$.
- **Packet sending:** $\alpha_i^{\mathbf{T}} = 50\,\text{nJ/bit}$ and $\alpha_i^{\mathbf{A}} = 100\,\text{pJ/bit}$ per m^2 in $\Gamma_{\mathbf{S}}(s_i, s_j, \lambda)$.
- **Packet receiving:** $\alpha_j^{\mathbf{R}} = 50\,\text{nJ/bit}$ in $\Gamma_{\mathbf{R}}(s_j, \lambda)$.

A sink is located not far from the bottom right of the sensing field. Regarding the distribution of sensors, we partition the sensing field into four equal regions, namely R1, R2, R3, and R4, and deploy a different number of sensors in each region. Three scenarios D1, D2, and D3 are considered, where Fig. 2 shows the proportion of the number of sensors in each region under each scenario.

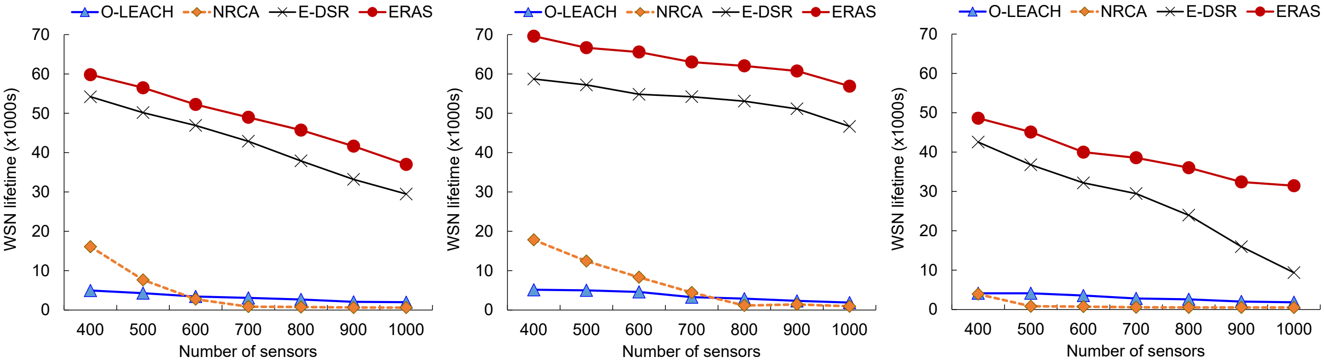
We choose three cluster-based routing methods mentioned in Section II for comparison. O-LEACH [20] is an improvement of LEACH, which selects CHs according to their residual energy and distances to the sink. Both NRCA [25] and E-DSR [28] divide the sensing field into grids. NRCA picks a sensor with the most energy to be the CH in each grid. On the other hand, E-DSR respectively splits and merges some grids to alleviate buffer overflow and facilitate data compression at CHs. Each CH can employ a data compression algorithm to condense packets received from its cluster members, where the data compression ratio is set to 0.5. Notice that O-LEACH asks CHs to straight send compressed packets to the sink. To achieve this, we extend the maximum communication range of a CH to 566 m ($\approx 400\,\text{m} \times \sqrt{2}$) in the O-LEACH method. For NRCA, E-DSR, and ERAS, the communication range of a CH is kept as 80 m (i.e., the same as an ordinary sensor). In the ERAS scheme, we set $C_{\min} = 2$ and $C_{\max} = 4$.

A. Comparison of WSN Lifetime

Fig. 3(a) presents WSN lifetimes of different methods in scenario D1, where sensors are evenly distributed throughout the sensing field. Overall, WSN lifetime abates as the number of sensors grows. Recall that WSN lifetime is calculated as the amount of time since the WSN starts operating until the first sensor drains of energy. When there are more sensors in the sensing field, some sensors will inevitably deplete energy more quickly because they have to relay more packets from upstream nodes. O-LEACH asks each CH to directly forward packets to the sink. Hence, those CHs far away from the sink have to consume more energy to send packets. That explains why O-LEACH results in a pretty low WSN lifetime. NRCA chooses a sensor possessing the most energy to be the CH in each grid and makes the sensor serve as the CH for a long time. When a grid has more sensors, the routing burden rises accordingly, forcing the CH to use up energy more quickly. Thanks to grid splitting and CH reelection, E-DSR can deal with the problem in NRCA and greatly raise WSN lifetime. In addition to reselect CHs depending on their energy statuses, our ERAS scheme adaptively picks multiple CHs to share the routing work in each grid. Consequently, ERAS can further improve WSN lifetime compared to E-DSR.

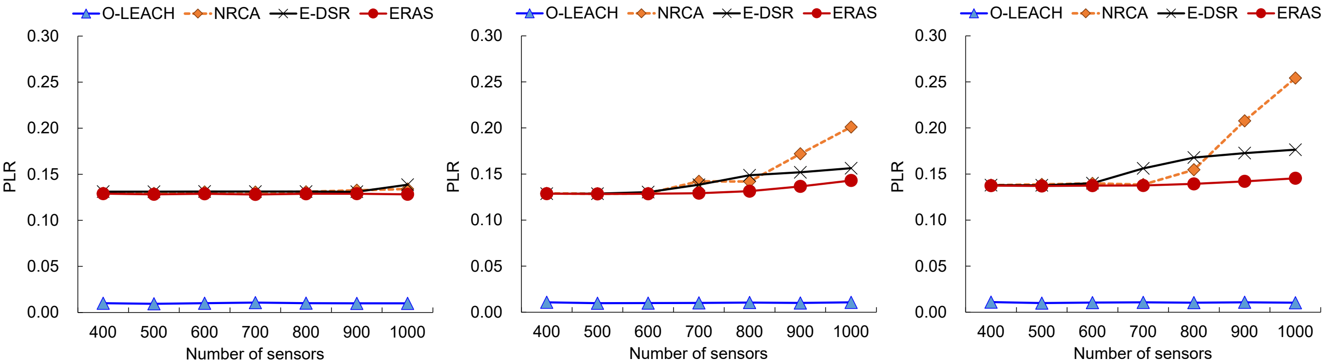
Fig. 3(b) compares the WSN lifetime of every method in scenario D2. In this scenario, the region adjacent to the sink (i.e., region R1) contains 30% of sensors in the WSN, which helps mitigate the energy hole problem. Thus, WSN lifetime can be significantly improved, especially for grid-based routing methods (i.e., NRCA, E-DSR, and ERAS). More specifically, as compared with scenario D1, O-LEACH, NRCA, E-DSR, and ERAS improve WSN lifetime by 11.80%, 58.71%, 27.52%, and 30.04%, respectively, in scenario D2. Evidently, our ERAS scheme has the highest WSN lifetime among all methods in scenario D2.

Then, Fig. 3(c) displays a comparison of WSN lifetime in scenario D3. In contrast to scenario D2, region R1 includes 10% of the WSN's sensors in scenario D3. It is conceivable that the energy hole problem in scenario D3 will get worse. In particular, compared with scenario D1, O-LEACH, NRCA, E-DSR, and ERAS reduce WSN lifetime by 6.24%, 74.34%, 35.45%, and 20.39%, respectively, in scenario D3. Moreover, NRCA always loses to O-LEACH. This phenomenon exposes the deficiency of traditional grid-based routing when region



(a) scenario D1 (b) scenario D2 (c) scenario D3

Fig. 3: Comparison of WSN lifetimes in different scenarios.



(a) scenario D1 (b) scenario D2 (c) scenario D3

Fig. 4: Comparison of PLRs in different scenarios.

R1 contains too few sensors. E-DSR uses dynamical grid partition to alleviate the above issue. However, its effectiveness will become worse when the number of sensors increases. As can be seen, the performance gap between E-DSR and ERAS significantly increases as the number of sensors grows. This result reveals the superiority of using multiple CHs by Eq. (1) to improve WSN lifetime in our ERAS scheme.

B. *Comparison of PLR*

Fig. 4(a) shows the PLR of every method in scenario D1. For cluster-based routing, packet loss is typically caused by data collision at underlying layers (e.g., MAC layer) or buffer overflow at CHs. Since O-LEACH may form many clusters and lets CHs directly send packets to the sink, the probability of buffer overflow is relatively low. Hence, O-LEACH has the lowest PLR among all methods. On the other hand, NRCA, E-DSR, and ERAS employ grid partition and select CH(s) to take charge of routing work for each grid. Since sensors are uniformly distributed in scenario D1, each grid could contain a similar number of sensors. Naturally, the chances of buffer overflow in these grid-based routing methods may be similar, thereby resulting in similar PLRs.

In Fig. 4(b), we present the PLRs of different methods in scenario D2. According to Fig. 2, region R4 contains 40% of the sensors in a WSN, which means that the sensor densities of those girds in R4 are high. As a result, when there are more than 800 sensors, the PLR of NRCA increases significantly. By splitting grids, the growth of PLR in E-DSR is slower than NRCA. Our ERAS scheme picks out more CHs for grids with high sensor densities, so it further reduces PLR than E-DSR. In particular, ERAS can reduce PLR by 11.29% and 5.82% compared with NRCA and E-DSR in scenario D2.

In scenario D3, there are two regions, R2 and R3, whose grids have high sensor densities. Hence, PLR's growth trend in Fig. 4(c) is similar to Fig. 4(b); in particular, packet loss in NRCA becomes more serious. Thanks to adaptively choosing multiple CHs via Eq. (1), ERAS can keep a lower PLR than both NRCA and E-DSR. Specifically, our ERAS scheme can respectively decrease PLR by 16.67% and 10.35% compared to NRCA and E-DSR in scenario D3.

VI. Conclusion

Sensors possess tiny batteries, but they shall keep sending data to a sink using multihop communication. Hence, energy-efficient routing is necessary to prolong a WSN's lifetime. In view that many cluster-based routing methods presume that sensors are evenly deployed in a sensing field, we propose the ERAS strategy that takes account of non-uniform distribution of sensors. ERAS divides the sensing field into grids, decides the last grid to reach the sink, and picks out multiple CHs in some grids to share the routing work. The selection of CHs considers not only the distribution of sensors in each grid but also their AREs. Depending on their energy statuses, sensors take turns to serve as CHs for balancing energy consumption. Simulation results reveal that the ERAS strategy substantially improves WSN lifetime as compared to O-LEACH, NRCA, and E-DSR methods. Besides, ERAS can keep a lower PLR than other grid-based methods (i.e., NRCA and E-DSR). For future work, we will consider that sensor densities may vary over time (e.g., caused by sensor mobility [33]).

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