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Optimistic Selection of Cluster Heads Based on Facility Location Problem in Cluster-Based Routing Protocols

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Abstract Cluster-based routing protocols are one of the most favorable approaches for energy management in wireless sensor networks. The selection of the best cluster heads (CHs), as well as the formation of optimal clusters, is an NP-hard problem. The present study proposes an optimal solution for CHs selection to generate a network topology with optimized network performance. The problem is formulated as facility location problem and a linear programming model is used to solve the optimization problem. Results of analysis o the network simulator (NS2) indicate that applying this method in cluster-based routing protocols prolongs 16 % of the network lifetime, increases 15.5 % of data transmission and improves 5.5 % of throughput, as compared to the results of current heuristic methods such as LEACH, DEEC and EDFCM protocols.

Keywords Clustering · Energy efficiency · Facility location problem · Wireless sensor networks · Heuristic method · Hierarchical routing protocols

1 Introduction

Wireless sensor networks (WSNs) have been increasingly exercised in various applications such as emergency response, medical treatment, target field, etc. [1,2]. A sensor network includes hundreds or thousands of cheap and low power sensor nodes deployed randomly in

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the network. Each sensor is capable of sensing the environment and sending information to the base station (BS). Due to limited and irreplaceable battery power of each sensor node, energy efficiency is one of the challenges in organizing sensor networks [3–6]. Different protocols and architectures have been proposed for large scale networks, from among which the hierarchical networks are more favorable than flat ones [7–10]. In hierarchical sensor networks, sensor nodes are organized into clusters with a cluster head (CH) and other typical nodes (non-CHs) in each cluster [11,12]. The CH collects data from cluster's member nodes, and then processes and transmits them to the BS [13,14]. Clustering is a mechanism to improve the performance of WSNs.Cluster-based routing protocols can be divided into two types: homogeneous and heterogeneous. Sensor nodes in homogenous WSNs have the same initial energy and identical capabilities. Generally, in cluster-based routing protocols; CHs are selected by a member of the cluster, based on some policies or predefined by a network designer. Furthermore, CHs can be selected in a self-organized manner from typical sensors or from sensors with richer resources [15]. In homogenous WSNs protocols, CHs are selected from among typical nodes. Due to high energy consumption of CHs compared to non-CHs, all capable sensor nodes try to be CH alternatively during the run time of network to prevent early expiration of CHs. On the contrary, in heterogeneous WSNs some sensor nodes have richer resources than the other ones and prefer to get the CHs roles. These networks can reorganize by adding some other sensor nodes easily when some nodes die. As mentioned, the formation of optimal clusters and selection of the appropriate CH in order to obtain a network topology with maximum coverage and high performance are NP-hard problems.

The simulation results indicate that some factors may lead to the formation of inefficient clusters, such as improper cluster distribution, the distances between the BS and CHs, inconsideration to both the nodes' positions and their energy consumption accordance with the nodes' roles. So in this paper, a new clustering method for WSNs is proposed that called "Probabilistic Selection of Cluster-Head Based on the Nearest Possible Distance of Cluster-Head (PSCND)" which is based on the facility location problem (FLP) [16] and it is modeled by a liner programming [17–22]. The results of simulations demonstrate that applying this method in clustering processes of other cluster-based routing protocols which do not consider the distances of CHs from each other, increases the network performance, prolongs the network lifetime, improves the network throughput and data transmission as compared with the current heuristic protocols. The paper is organized as follows: Sect. 2 provides related works. Section 3 discusses the PSCND method and formalizes the clustering problem. Section 4 shows the performance of the PSCND and validation of the analysis. Finally, Sect. 5 gives concluding remarks.

2 Related Works

There are many studies concerning the efficient cluster formation for WSNs. The well known cluster-based routing protocols are LEACH [23,24], TEEN [25], APTEEN [26], PEGASIS [27], DEED [28,29], and EDFCM [30]. In most of them, some sensor nodes are selected as CHs for gathering data from other nodes and sending them to the BS. Some of the energy efficient protocols are studied here.

The low energy adaptive clustering hierarchy (LEACH) protocol is the most known and also one of the first hierarchical routing protocols in WSNs. LEACH minimizes energy distribution in sensor networks. It randomly selects sensor nodes as CHs without any negotiation with the other sensors. LEACH uses single-hop routing where each node can directly transmit data to the CH. Results of LEACH indicate that if the number of clusters be 5 % of all nodes, the best results will be achieved [23,24]. Handy et al. modified the CH selection algorithm originated from LEACH protocol to reduce the overall energy consumption of the network. In the process of selecting a proper CH, the algorithm considers the residual energy of nodes and also improves the network energy-balancing which leads to increase the network lifetime. The distributed energy efficient clustering (DEEC) protocol is similar to LEACH, but it uses residual energy of each node and the average energy of the network in clustering process. Reducing overall energy consumption of the network in order to increase its lifetime is an important issue that these algorithms pay attention to it [28,29]. Node proximity has been used in a number of recent studies in which the closest sensor nodes to a CH are chosen as its member nodes in order to minimize the total energy consumption [31–35]. However, since direct data transmission of nodes which lay far from the BS consume a great amount of energy, some approaches use multi-hop methods to reduce energy consumption [23,31]. The energy efficient unequal clustering (EEUC) protocol addresses energy efficiency and uses a multi-hop connection technique to connect CHs to the BS [36]. It uses clusters with unequal sizes in order to balance the load among the nodes which are near to the BS. The energy dissipation forecast and clustering management (EDFCM) is a new protocol with energy and computational heterogeneity in heterogeneous WSNs. This protocol considers the residual energy and energy consumption rate in all nodes to guarantee the reliable transmission, improve the clustering scheme, prolong the network lifetime and balance the energy consumption better than the conventional routing protocols [30]. The distance-energy cluster structure algorithm (DECSA) is a distributed competitive unequal clustering algorithm; it considers both the distance and residual energy information of nodes. DECSA protocol devotes a random number to each node that is called ID and selects the CHs based on the network density to minimize the number of CHs while maintaining the whole network coverage properly [37]. Liu et al. designed a distributed energy-efficient clustering with improved coverage (DEECIC) protocol that considers communication energy consumption and updates CHs based on the joint information of nodes' residual energy and distribution. The goal of DEECIC is clustering with the least number of CHs to cover the whole network and assigning a unique ID to each node based on local information [38]. Most of existing methods increase network lifetime but they cannot guarantee the whole network coverage [39–41]. Several studies deal with optimal location of the BS in cellular and wireless networks to cover network area satisfactorily. The BS location problem is an instance of a facility location problem (FLP). The FLP has been applied in a large number of other applications such as locating warehouses or factories to service retail outlets, locating of fire stations and hospitals in a city, designing of star topology network, clustering for increasing network lifetime and forming optimal clusters, aggregator placement for electing nodes as aggregators. These are instances of FLP and like other optimization problems, are NP-hard problems [16,21,22]. In FLP, sensors and the BS correspond respectively to a set of demand points and a set of facilities to satisfy a certain purpose. The maximal covering location problem (MCLP) is referred to as a location-allocation problem since each demand point must be assigned to a certain sensor [42,43]. FLP is solved by approximation algorithms, heuristic method [17–20] or linear programming model to get an optimal solution [16,17,22]. Linear programming is used by Chakrabarty [44], and different greedy heuristic rules are suggested to deploy the sensors [45–47]. Linear programming is the most frequently applied operations research technique. A linear programming model represents real world situations with some sets of parameters determined by experts and decision makers while in real world applications certainty, reliability and precision are often illusory concepts. Conversely, non-liner programming or meta-heuristics methods are complex and need complex knowledge.This paper proposes PSCND method for CHs selection that focuses on CHs distribution. PSCND formulates the optimal CHs selection as a linear programming model, which has been proved to be an NP-hard and is an instance of FLP optimization problem that leads to improve network topology and increase network performance.

3 Statement of the Problem

In this section, the significance of introducing the proposed method of PSCND is explained. According to the nature of WSN, an important factor in the network topology and the clustering is CHs selection. As mentioned, there are different protocols for clustering in WSNs [23–29,31–35]. They generally disregard the effect of the distances among CHs and roles of nodes that lead to considerable difference in energy consumption levels of nodes which are close to the CHs and those that lie farther from CHs, and sometimes lead to cluster overlapping and redundant data transmission to the BS. According to the radio energy consumption model, energy distribution depends on the distance between the transmitter and the receiver. In the best mode, based on free space model energy required to transmit data alongside the channel is proportional to its square distance from the target node [48]. In single-hop sensor networks, energy consumption of CHs that lie far from their member nodes might be much more than those which are closer to their member nodes; they lose more energy and the clusters expire earlier. These protocols apply controlling methods which lead to different energy levels; consequently, high delay is imposed on the network and network scalability is impugned. By inappropriate CHs selection, cluster overlapping occurs and data gathering process becomes less effective due to redundant data transmission towards the BS. Additionally, this may cause division of network into active and inactive areas. An inactive area is a region in which no data is transmitted to the BS and is not covered completely despite being part of the network. Inactive area can be occurred in network due to early demise of sensor nodes because of lack of battery, presence of an obstacle between the nodes and the BS, and death of CHs due to lack of sufficient energy. In Active area, sensor nodes have sufficient amount of energy to send data to the CHs or BS. Considering the above descriptions, it can be concluded that each cluster has an area in which the presence of other CHs would lead to extra operations, less energy efficiency, congestion, interference among data signals, and redundant data transmission. This area is called forbidden area. The two neighbor clusters would have no overlap when the distance between them is greater than the summation of their boards, otherwise they would overlap. The distance between a CH and the farthest node in a cluster is the board of that cluster.

In Fig. 1, R1 and R2 are the cluster boards and d is the distance between two nearby CHs. Clusters have no overlap when d is greater than R1 + R2. In other words, if the distance between CHs is less than R1 + R2, CHs might be selected in the forbidden area of other

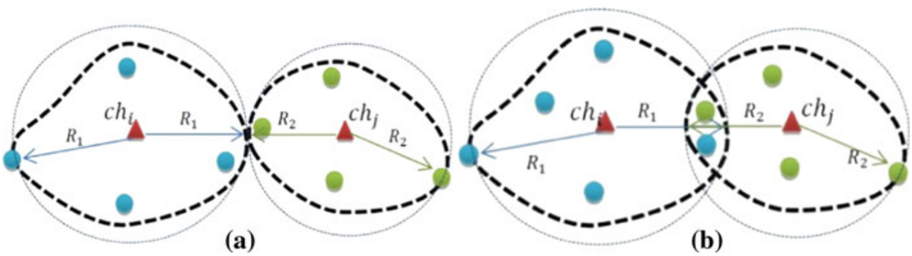


Fig. 1 **a** Independent clusters. **b** Overlapped clusters

clusters, as shown in Eq. (1). $o\left|\mathrm{area}_{ch_i} \cap \mathrm{area}_{ch_j}\right|$ is the common area in which clusters overlap. area_{ch_i} and area_{ch_j} are the cluster areas of ch_i and ch_j, respectively.

$$\begin{aligned} &\text{if } d \geq R_1 + R_2 \quad \text{then } o\left|\mathrm{area}_{ch_i} \cap \mathrm{area}_{ch_j}\right| = \emptyset \\ &\text{if } d < R_1 + R_2 \quad \text{then } o\left|\mathrm{area}_{ch_i} \cap \mathrm{area}_{ch_j}\right| \neq \emptyset \end{aligned} \tag{1}$$

3.1 Network Model

Sensor networks can be modeled as an undirected graph $G = (V, E)$, where V is the set of vertices or sensors and E is the set of edges or links between sensors. In the following, there are some assumptions about the sensor nodes and the network model.

Network size (N) is a number of sensor nodes deployed in an area, $N = |V|$, since the area is fixed, a change in network size can create a change in network density, $\mu = \frac{N}{l^2}$. The area is a square with the length side of l. The sensor nodes are scattered randomly in the region of interest and all nodes are fixed. Cluster board (R) is the maximum distance between the farthest node of a cluster with its related CH.

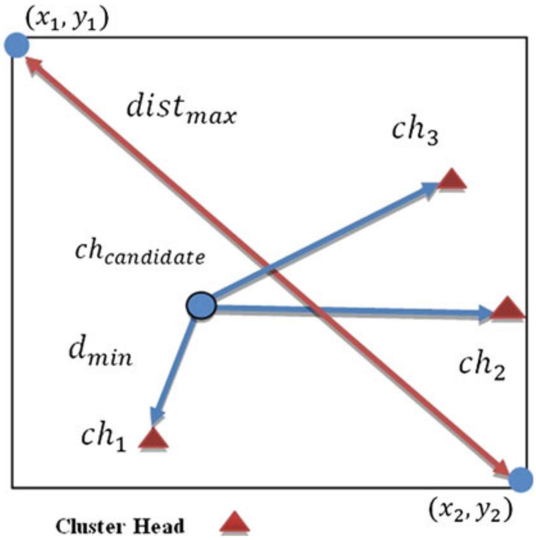
3.2 CH Detection Model

As reviewed, one of the important challenges in WSNs is the formation of optimal clusters. The accurate and proper CH selection is an important factor in optimal cluster formation which is an NP-hard problem. The clusters should have the minimum overlapping to avoid redundant data transmission and energy wastage. PSCND provides high quality of service in networks by selecting CHs in a proper distance from each other. In this method, each CH is selected from among nodes which are not located in the forbidden area of other clusters. The clusters must be formed in a way that they do not have any common areas and avoid high differences in energy levels of sensor nodes. To overcome the drawbacks mentioned above, proposed method formulates the clustering problem as a FLP where the objective is to distribute the CHs appropriately. FLP makes the CH selection process more flexible.

In general, the input to the metric FLP consists of a set of facilities F, a set of demands D, a facility cost f_i for each $i \in F$, and a metric that defines service costs c_{ij} for each $i, j \in F \cup D$. Feasible solutions must assign each client to a facility. An optimal solution to the facility location problem is a feasible solution of minimum cost [16,21,22].

Here, an undirected graph $M = (V_{CH}, E_{CH})$ is introduced to select CHs. That M is a subgraph of graph G, $V_{CH} = \{ch_1, ch_2, \ldots, ch_n\}$, $E_{CH} = \{(ch_i, ch_j)\}$, $1 \leq i \leq n$, $1 \leq j \leq n$, $i \neq j$. Any subset of nodes, $V_{CH} \subseteq V$, forms the vertices set of graph M that includes two subsets; CH and $CH_{Candidate}$. Where $CH = \{ch_1, ch_2, \ldots, ch_m\}$, $m \leq n$,correspond to the facilities and $CH_{candidate} = \{ch_1, ch_2, \ldots, ch_k\}$, $k \leq n$ correspond to the demands, $V_{CH} = CH \cup CH_{candidate}$. Candidate nodes are that kinds of nodes which are being examined in order to become CHs and they have competency of being CHs in each round. However, it should be borne in mind that the potential candidate nodes for CH must be active nodes with sufficient amount of energy; and initially should not have been selected as CH in previous rounds. They investigate the proper situation proportional to the protocol and clustering procedure to be CHs. E_{CH} is the set of links that connect members of V_{CH} to each other, $E_{CH} \subseteq E$. Here, the length of an edge $d = \left(ch_i, ch_j\right) \in E_{CH}$ is denoted by $\left|d_{ij}\right|$ where $\left|d_{ij}\right| = \left|ch_i - ch_j\right|$ equals the Euclidean distance from ch_i to ch_j. It should be noted that, depending on network topology, CHs can be selected in a synchronously or asynchronously. According to FLP,

Fig. 2 The depiction of indicator function



the facilities correspond to the CHs and the demands points correspond to the candidate nodes. Also, a cost function is defined based on problem objectives Cost function should select CHs from among candidate nodes in order to form optimal network topology.

In Fig. 2, $CH = \{ch_1, ch_2, ch_3\}$ corresponds to facilities and $CH_{candidate}$ node corresponds to the demand. Among deployed nodes in the network, a node is randomly selected as the first CH, for further selection of CHs, the nearest distances between CHs and candidate node is computed as Eq. (2), then it is divided by the maximum possible Euclidean distance between CHs.

$$d_{min}(ch_i) = \min dist(ch_i, ch_j) \quad \forall ch_j \in CH, ch_i \in CH_{candidate} \tag{2}$$

Then, the obtained result powers to α and it is called indicator function $Q(ch_i)$ which is defined by Eq. (3):

$$Q(ch_i) = \left(\frac{d_{min}(ch_i)}{dist_{max}}\right)^{\alpha} \quad ch_i \in CH_{candidate} \tag{3}$$

The effect of the distance parameter in selecting CHs in this technique is determined by the parameter α, which is a positive real number, and the value of this parameter is achieved from the result of analyses and simulations. The $Q(ch_i)$ makes the CH selection procedure more flexible. Its goal is controlling and managing distance among CHs in regard to each other. This function prevents selecting CHs in forbidden area, early dead nodes and formation of inactive area. As mentioned, the most important objective of PSCND is the optimal CHs distributions with minimum overlapping and maximum network coverage. For formal expression it is modeled by linear programming. Some constraints of model are assumed in formulas that are expressed by binary variables [22,49,50]. If nodes i and j become CHs, $y_{ij} = 1$, otherwise, $y_{ij} = 0$. $dist_{ij}$ equals to the Euclidean distance between nodes i and j. L is lower bound on the distance between each CH nodes H is the upper bound on the distance between each CH nodes. α is a positive real number between 0 and 1. The selection of CH is done more flexible by α. The objective can be expressed as Eq. (4) and the constraints of model can be formulated as follows:

$$\min\left(\sum_{\substack{i,j=1\\ j>i}}^{n} \mathrm{dist}_{ij}^{\alpha} y_{ij}\right) \tag{4}$$

s.t.

$$\sum_{\substack{i,j=1\\ j>i}}^{n} y_{ij} = K_{CH} \tag{5}$$

$$y_{ij} \le \sum_{k>j}^{n} y_{jk} \qquad \forall i,j = 1\ldots n, j > i \tag{6}$$

$$\sum_{k>j}^{n} y_{jk} \le 1 \qquad \forall j = 1\ldots n \tag{7}$$

$$y_{ij} = 0 \qquad \forall i,j = 1\ldots n, i \ge j \tag{8}$$

$$L < \mathrm{dist}_{ij}^{\alpha} y_{ij} < H \quad \forall i,j = 1\ldots n, j > i \tag{9}$$

$$0 \le \alpha \le 1 \tag{10}$$

$$y_{ij} \in \{0,1\} \qquad \forall i,j = 1\ldots n, j > i \tag{11}$$

Equality (5) denotes the number of CHs, which are a fraction of all sensor nodes in the network. Constraints (6), (7), and (8) ensure that the node i connects to node j and avoid repeated selections. Inequality (9) ensures upper and lower bounds on the distance between each CH nodes that assigns a condition for the distance of each two nodes and defines the ranges of CHs locations and forbidden areas. In order to minimize the overlapping, the distances among CHs should be more than L and for maximizing the network coverage the distances among CHs should be less than H. Constraint (10) is a condition for defining the distances between each two CHs. This linear programming model acknowledges that in addition to nodes' positions to each other, some other parameters are also impressive in CHs selection, including number of CH nodes, cluster board, and α parameter. The PSCND' linear programming model guarantees that for $\alpha > 0$, there is the minimum distance L between each two nodes. The distance parameter is ineffective in clustering process when $\alpha = 0$.

3.3 Applying PSCND in the Cluster-Based Routing Protocols in Homogeneous and Heterogeneous WSNs

3.3.1 PSCND in Homogeneous WSNs

LEACH [23,24] is based on clustering in which time is split into equal length time spans called rounds. Each round includes two phases. The first phase is called set-up phase which is the cluster formation phase. In the second, steady-state phase, data transmission starts. In the set-up phase, CHs are selected and each node chooses a random number between 0 and 1. The random numbers are compared with threshold T(i). If it is less than the T(i), the node becomes a CH in the current round, Eq. (12). r is the number of current round. G is the set of nodes which have not been chosen as CH in previous rounds. N is the number of network nodes. k is the average number of CHs in each round.

$$T(i) = \begin{cases} \dfrac{k}{(N-k)\times\left(r \bmod \frac{N}{k}\right)} & \text{if } i \in G \\ 0 & \text{otherwise} \end{cases} \tag{12}$$

In LEACH protocol all sensor nodes initially have same energy levels. Experiments show that LEACH, as a hierarchical routing protocol, can save more energy than the plane multi-hop routing protocols and the static network clustering algorithms. The most important drawback of LEACH is that it does not ensure a proper CHs distribution and optimal clusters formation. Also it does not consider the nodes' residual energy, which leads to early death of some nodes and the overall invalidity of the network. By applying the proposed method, PSCND, in LEACH protocol, candidate nodes compare their positions with other existing CHs in the set-up phase before the next round of CH selection begins. In the first round of LEACH protocol, PSCND has no effect on clustering formation and the CHs are selected based on LEACH protocol. But from second round, candidate nodes begin their operations. First the distance between the candidate node and the nearest CH node is calculated and then it is divided by the maximum distance between the two farthest nodes in network then it powers to α, in accordance to the indicator function $Q(ch_i)$, Eq. (3). PSCND-LEACH guarantees that there are average $P_{opt}N$, CHs in every round the same as LEACH. It allows each node to become a CH once in $n_i = \frac{1}{P_{opt}}$ rounds. n_i denotes the number of rounds to be a CH. PSCND-LEACH uses the same energy model as LEACH [23,24]. The PSCND-LEACH threshold, $T_{pl}(ch_i)$, is defined by applying the Eq. (3) to the Eq. (12), as follows:

$$T_{pl}(ch_i) = \begin{cases} \dfrac{k}{(N-k)\left(r \bmod \frac{N}{k}\right)} \left(\dfrac{d_{min}(ch_i)}{dist_{max}}\right)^{\alpha} & \text{if } ch_i \in CH_{candidate} \\ 0 & \text{otherwise} \end{cases} \tag{13}$$

As explained, in addition to the criteria of LEACH, some other parameters are considered in selecting CHs in PSCND-LEACH. These parameters are the α parameter, nodes' locations and the distances of CHs from each other. The results show that employing PSCND in LEACH protocol leads to a proper CHs distribution and improves qualitative parameters of the network.

3.3.2 PSCND in Heterogeneous WSNs

The proposed PSCND model can be applied in the clustering routing protocols in heterogeneous WSNs. These protocols generally consider the residual energy and the rate of energy consumption besides the initial energy of all sensor nodes in CHs selection processes. In the following after introducing two well known heterogeneous DEEC and EDFCM protocols, the effects of PSCND on these protocols are studied.

In DEEC protocol, CHs are selected based on the ratio of residual energy of each node and average energy of the network [28,29]. Two-level heterogeneous and multi-level heterogeneous networks are two types of heterogeneous networks. There are two types of nodes in two-level heterogeneous networks; normal and advanced nodes. E_0 is the initial energy of the normal nodes and m is a fraction of advanced nodes which own β times more energy than normal nodes. There are mN advanced nodes equipped with initial energy of $E_0(1+\beta)$ and $N(1-m)$ normal nodes equipped with initial energy of E_0. So, total initial energy for two-level heterogeneous networks is computed by Eq. (14):

$$E_{total} = N(1-m)E_0 + NmE_0(1+\beta) = NE_0(1+\beta m) \tag{14}$$

In multi-level heterogeneous networks, initial energy of nodes is randomly selected in the range of $\left[E_0, E_0(1+\beta_{max})\right]$. Thus, total initial energy is given by Eq. (15):

$$E_{total} = \sum_{i=1}^{N} E_0\,(1+\beta_i) = E_0\left(N + \sum_{i=1}^{N} \beta_i\right) \tag{15}$$

Each node i uses T (i) to determine whether it is a CH in each round or not, Eq. (16).

$$T\,(i) = \begin{cases} \frac{p_i}{1-p_i\left(r \bmod \frac{1}{p_i}\right)} & \text{if } i \in G \\ 0 & \text{otherwise} \end{cases} \tag{16}$$

where G is the nodes set that are eligible to be CHs at round r. Let $p_i = \frac{1}{n_i}$, which can be also regarded as average probability, to be a CH during n_i rounds. In DEEC, n_i is chosen based on the residual energy of nodes at round r.

Therefore, p_i is defined by Eq. (17):

$$p_i = \begin{cases} \frac{p_{opt} E_i(r)}{(1+\beta\, m)\overline{E(r)}} & \text{if i is the normal node} \\ \frac{p_{opt}(1+\beta) E_i(r)}{(1+\beta\, m)\overline{E(r)}} & \text{if i is the advanced node} \end{cases} \tag{17}$$

p_{opt} is the optimal percentage of nodes that want to become CHs in each round. $E_i(r)$ is the residual energy of node i and $\overline{E(r)}$ is the average energy of the network at round r, Eq. (18).

$$\overline{E(r)} = \frac{1}{N}\sum_{i=1}^{N} E_i(r) \tag{18}$$

Employing PSCND method in the DEEC protocol requires some other parameters such as the α parameter, the nodes' locations and CHs distances from each other in addition to the parameters of initial and residual energy of the nodes themselves and the average energy of the network in the set-up procedure of DEEC. These considerations improve the clustering and the network topology. Similar to DEEC, PSCND-DEEC can be exerted to heterogeneous WSNs with normal and advance nodes. Hence, energy model distribution model in PSCND-DEEC is the same as DEEC and the average energy is computed by Eq. (18). PSCND-DEEC selects CHs based on the nodes' locations and the CHs' positions. For guaranteeing the proper CHs distribution, the DEEC threshold in Eq. (16) is changed to Eq. (19) for the threshold of PSCND-DEEC.

$$T_{pd}\,(ch_i) = \begin{cases} \frac{p_i}{1-p_i\left(r \bmod \frac{1}{p_i}\right)}\left(\frac{d_{min}(ch_i)}{dist_{max}}\right)^{\alpha} & \text{if } ch_i \in CH_{candidate} \\ 0 & \text{otherwise} \end{cases} \tag{19}$$

So, it is expected that the new threshold $T_{pd}\,(ch_i)$, improves the network quality of service parameters.

EDFCM [30] is another heterogeneous cluster-based routing protocol in which PSCND is applied in its clustering and CH selection processes. EDFCM assumes that network includes three types of nodes; type_0, type_1, and the management nodes. The type_0 and type_1 nodes, called sensing nodes, are responsible for performing various tasks and transmitting the collected data to the destination, and the management nodes provide the management information about clusters for the two types of nodes. E_0 is the initial energy of the type_0 and m is a fraction of type_1 nodes which own β times more energy than type_0 nodes.

There are mN, type_1 nodes equipped with initial energy of $E_0\,(1+\beta)$. In EDFCM protocol, operation of the network can be divided into two phases: cluster formation phase and data collection phase. In each round, when CH is a type_0 node, its energy dissipation is different from the case that the CH is a type_1 node. Also different weighted probabilities for the two types of nodes are defined by Eqs. (20) and (21):

$$p_{type0} = \frac{p}{1+\beta\,m} \tag{20}$$

$$p_{type1} = \frac{p}{1+\beta\,m}\,(1+\beta) \tag{21}$$

This protocol assumes that the energy dissipation in subsequent rounds is correlative. EDFCM uses the average energy consumption of the two types of CHs in previous round as the forecast values for their energy consumption in the next round. The more residual energy in a node after the operation of next round, the higher probability the node will be selected as a CH. Thus, the weighted probabilities for the selection of CHs are defined by Eq. (22):

$$p_i = \begin{cases} \frac{p}{1+\beta m}\left(\frac{E_i(r)-E_{PR\_T0}(r)}{\bar{E}(r+1)}\right) & \text{if node i is a type\_0 node} \\ \frac{p}{1+\beta m}(1+\beta m)\left(\frac{E_i(r)-E_{PR\_T1}(r)}{\bar{E}(r+1)}\right) & \text{if node i is a type\_1 node} \end{cases} \tag{22}$$

where $E_i(r)$ is the residual energy of node i in round r. The average energy consumption of the two types of CHs in round r are defined by Eqs. (23) and (24):

$$E_{PR\_T0}\,(r) = \frac{1}{N_{type0}} \sum_{i=1}^{N_{type0}} E_{CH\_T0(i)}\,(r) \tag{23}$$

$$E_{PR\_T1}\,(r) = \frac{1}{N_{type1}} \sum_{j=1}^{N_{type1}} E_{CH\_T1(j)}\,(r) \tag{24}$$

where $E_{CH\_T0(i)}\,(r)$ and $E_{CH\_T1(j)}\,(r)$ are the energy consumption of CH nodes i and j in the r round, and N_{type0} and N_{type1} are the number of different types of CHs in the current round.In the network model, since the nodes are scattered uniformly in the network, $\overline{E}(r+1)$ is the average energy of nodes in $r+1$ round and it is computed by Eq. (25):

$$\overline{E}\,(r+1) = \frac{1}{N} E_{total}\left(1-\frac{r+1}{R}\right) \tag{25}$$

$$E_{total} = NE_0\,(1+\beta\,m) \tag{26}$$

where E_{total} is the total initial energy and R is an estimated value of the network lifetime, Eq. (26). E_{round} denotes the consumed energy of the network in each round. R can be approximated by Eq. (27):

$$R = \frac{E_{total}}{E_{round\_total}} \tag{27}$$

By applying PSCND in the clustering process of EDFCM protocol, $T_{pe}\,(ch_i)$ is calculated by Eq. (28). Similar to EDFCM, PSCND-EDFCM clustering is done in cluster formation phase. But in this method a constraint is added in selection of the nodes in both types (type_0 and type_1), in which the node should be a member of the candidate nodes set. PSCND adds the α parameter, the nodes' locations and CHs distances from each other to the EDFCM criteria, which are the residual energy, the nodes' energy consumption rates and forecasting of energy consumption, to select optimum number of CHs per each round, in addition to more energy conservation and network lifetime prolongation.

$$T_{pe}(ch_i) = \begin{cases} \frac{p}{1+\beta m}\left(\frac{E_i(r)-E_{PR\_T0}(r)}{\bar{E}(r+1)}\right)\left(\frac{d_{min}(ch_i)}{dist_{max}}\right)^{\alpha} & \text{if } ch_i \text{ is a type}_0 \text{ node, } ch_i \in CH_{candidate} \\ \frac{p}{1+\beta m}(1+\beta x)\left(\frac{E_i(r)-E_{PR\_T1}(r)}{\bar{E}(r+1)}\right)\left(\frac{d_{min}(ch_i)}{dist_{max}}\right)^{\alpha} & \text{if } ch_i \text{ is a type}_0 \text{ node, } ch_i \in CH_{candidate} \end{cases} \tag{28}$$

The energy model of PSCND-EDFCM is the same as EDFCM, and the average energy consumption of the two types of CHs in PSCND-EDFCM, $E_{PR\_T0(i)}(r)$ and $E_{PR\_T1(j)}(r)$, are computed by Eqs. (23) and (24).

The results of analysis indicate that applying the proposed method, PSCND, in EDFCM can improve the network topology and the cluster formation. It is expected that by employing PSCND in the present protocols, which do not consider CHs distribution in their clustering processes, optimal clusters will be formed and CHs will be distributed uniformly in the network. Also, PSCND prevents cluster overlapping and CHs aggregation, and improves network performance in terms of energy efficiency, network scalability, network lifetime, and data transmission. The following section gives the evaluation remarks.

4 Performance Analyses

In this section the effect of PSCND on clustering processes of cluster-based routing protocols in WSNs, which do not consider the distance factor among CHs, is studied. In the proposed method, CH selection is dependent on the parameters such as the α parameter, the maximum possible distance between sensor nodes in the network, the distances between candidate nodes and CHs, the cluster boards, and the node numbers. In order to analyze the proposed method, PSCND's linear programming model is solved via MATLAB in Sect. 4.1, to investigate its performance and effect on CH selection. In Sect. 4.2 implementation of PSCND in LEACH, DEEC, and EDFCM protocols are simulated by NS2 and results are analyzed.

4.1 PSCND Network Topology Simulated by MATLAB

PSCND algorithm, along with its linear programming, is simulated in MATLAB to obtain an accurate solution. Figure 3 is an example of network topology for CHs selection in PSCND. In this example, $N = 100$ nodes are scattered randomly in a 1000 m $\times$ 1000 m square area, all cluster boards are assumed equal, and the α value is set larger than zero, $\alpha > 0$. Figure 3a shows that the dispersion of CHs in PSCND gives the best result for $\alpha = 0.15$. Figure 3b shows the result of solution in linear programming that gives the best result for $\alpha = 0.2$. The difference between α values is because of the random selection of the first CH in PSCND, whereas the next CHs are selected based on the first one, but its linear programming model selects all CHs synchronously. Therefore, the optimal α value which is obtained from analyses and simulations in various clustering algorithms is 0.15 and it is obtained 0.2 in linear programming model.

4.2 Evaluation of PSCND Performance in Network Simulation (NS2)

Here, the performance of PSCND in LEACH, DEEC, and EDFCM protocols is evaluated via NS2 in homogeneous and heterogeneous networks. Radio model for energy consumption in

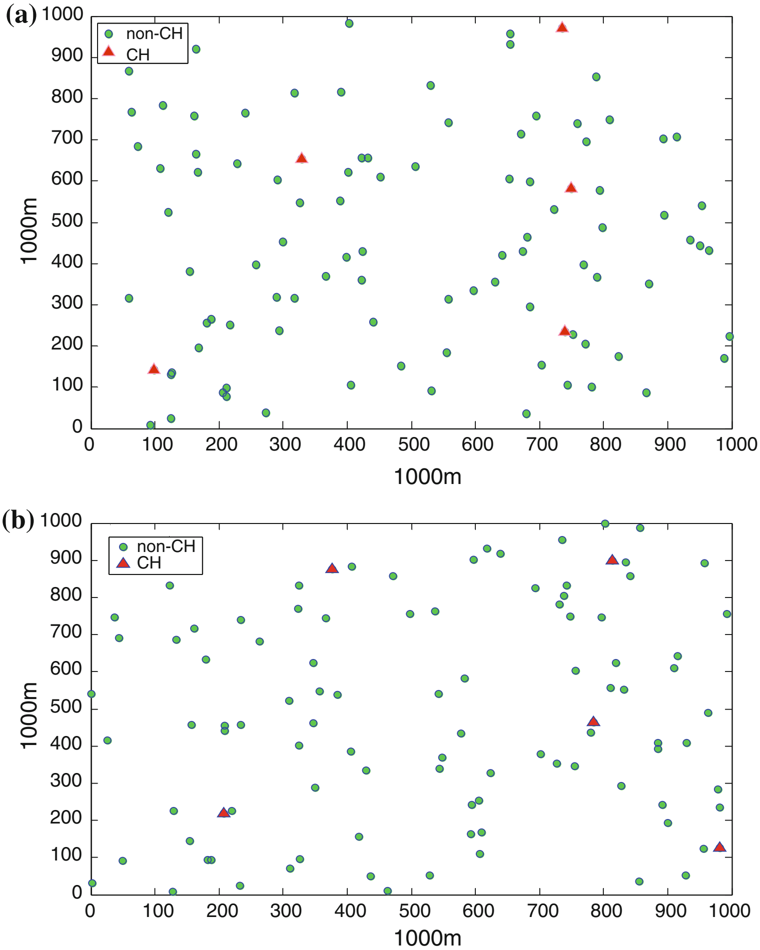


Fig. 3 Network topology. **a** Uniform distribution by PSCND. **b** Uniform distribution by linear programming

sensor network is the same as radio model discussed in LEACH [23,51]. It is assumed that the radio channel is symmetric and sensors are fixed and uniformly deployed in a $M \times M$ field; moreover, all of the sensors always have data to send to the BS. In order to evaluate clustering processes of other protocols using this method, it is supposed that environment is error-free and the effects of collision and interference are ignored. Some parameters used in simulation are introduced in Table 1. Where E_{elec} is the energy dissipated per bit to run the transmitter or the receiver circuit, and ε_{fs} or ε_{mp} is the amplifier energy that depends on the transmitter amplifier model. p_{opt} is the optimal probability of a node to become a CH. In the clustering routing protocols for homogeneous networks like LEACH, it is assumed that all sensor nodes have the same initial energy, E_0. On the contrary, in the heterogeneous networks, different types of sensor nodes have different initial energy levels. DEEC and EDFCM protocols define the normal nodes with the same initial energy, E_0 and the advanced nodes own β times more energy than the normal ones, E_0 $(1 + \beta)$. The α parameter is an optimization parameter that is proposed by PSCND and is varied in the range of (0, 0.3].

Table 1 Simulation parameters

Description	Symbol	Value
Network size	$M \times M$	1000 m $\times$ 1000 m
Node numbers	N	50, 75, 100, 125, 150, 175,200
Transmit amplifier if $d_{BS} \leq d_0$	ε_{fs}	10 pJ/bit/m^2
Transmit amplifier if $d_{BS} \geq d_0$	ε_{mp}	0.0013 pJ/bit/m^4
Data aggregation energy	E_{DA}	5 nJ/bit/message
Transmitter/receiver energy	E_{elec}	50 nJ/bit
Initial energy of each node	E_0	0.5 J
Optimization parameter	α	(0, 0.3]
An integer number	β	1
Optimal node percentage to be CHs	p_{opt}	0.1

Each experiment is repeated 20 times for every scenario, and all experiments are conducted with different α values and different densities.

The following concepts are the bases of the network lifetime, the data transmission, and the network throughput that are defined as the evaluation parameters in this paper. Network performance has various definitions for various networks with different applications and data types. One of the methods of determining the performance of a network is to measure the amount of data delivered to the BS. Actually, the more the BS receives data, the more its control over the environment increases [52–54].Lifetime is one of the criteria for evaluating the performance of routing protocols in sensor networks and, based on its applications, has different definitions in different networks [31,55]. In this scenario, network lifetime is the minimum number of alive nodes which is required for the network to be active. Network throughput is the parameter that evaluates the network performance and depends on both the amount of data transmission and network lifetime [55–57].

4.2.1 Comparison of Network Lifetime and Data Transmission in Homogeneous and Heterogeneous Networks

The effect of applying PSCND method is investigated on the network lifetime (Figs. 4a, 5a, 6a) and data transmission (Figs. 4b, 5b, 6b) in clustering process of LEACH, DEEC and EDFCM protocols in this subsection. These diagrams demonstrate that sensor networks with various densities have different optimal α values. The diagrams reach their maximum points in different scenarios at these optimal values. So, obtaining an optimal α value in sensor networks with various densities leads to maximum performance of the network.

PSCND-LEACH protocol is a homogeneous network similar to LEACH; thus, all nodes have the same initial energy, E_0. In LEACH protocol, energy distribution is not done properly; because the energy consumption rates are various in the sensor nodes depend on their roles (i.e. CHs consume more energy than members, so their death is earlier than others). By applying PSCND method in the set-up phase of LEACH protocol, these drawbacks are minimized. PSCND-LEACH considers the nodes' locations and the distances between CHs in the network as Eq. (3). Proposed method changes the CHs selection threshold of LEACH from Eqs. (12) to (13). Results of Fig. 4a, b indicate that PSCND-LEACH have maximum network lifetime and data transmission respectively, for $N = 50$, 75, and100 when $\alpha = 0.1$.

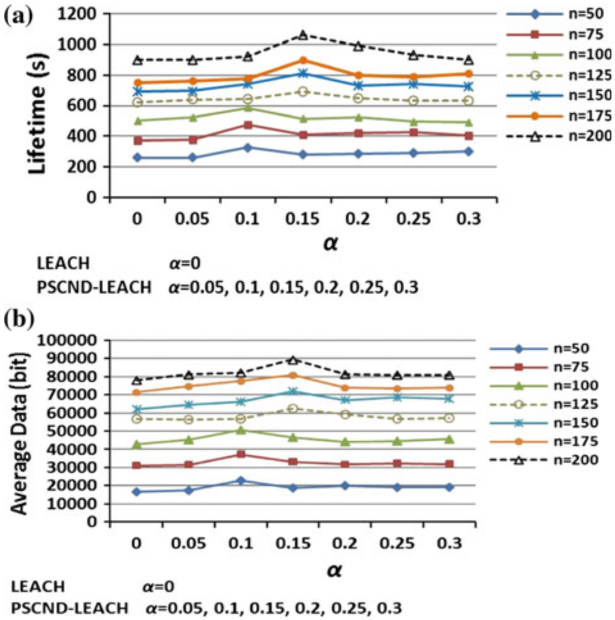


Fig. 4 Comparing of LEACH and PSCND-LEACH. **a** Network lifetimes. **b** Data transmission

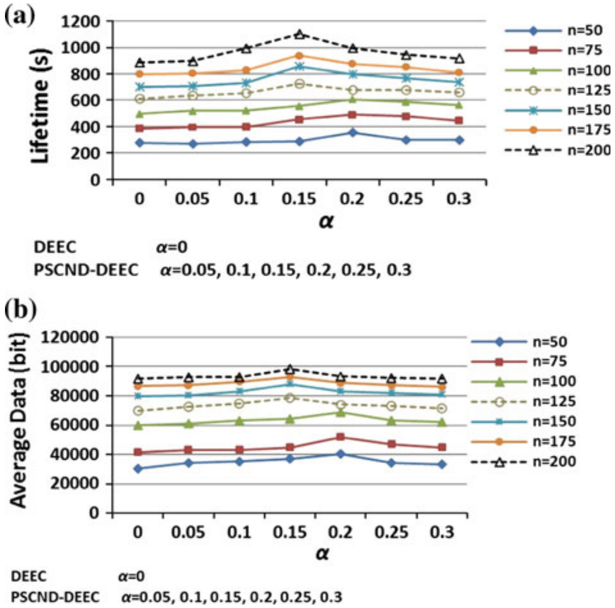


Fig. 5 Comparing of DEEC and PSCND-DEEC. **a** Network lifetimes. **b** Data transmission

Also, in high dense networks such as $N = 125, 150, 175,$ and 200, maximum performance in both evaluation parameters is achieved for $\alpha = 0.15$.

Figures 5a, b show effects of various α values and node numbers on the network lifetime and data transmission respectively, in the PSCND-DEEC and DEEC.

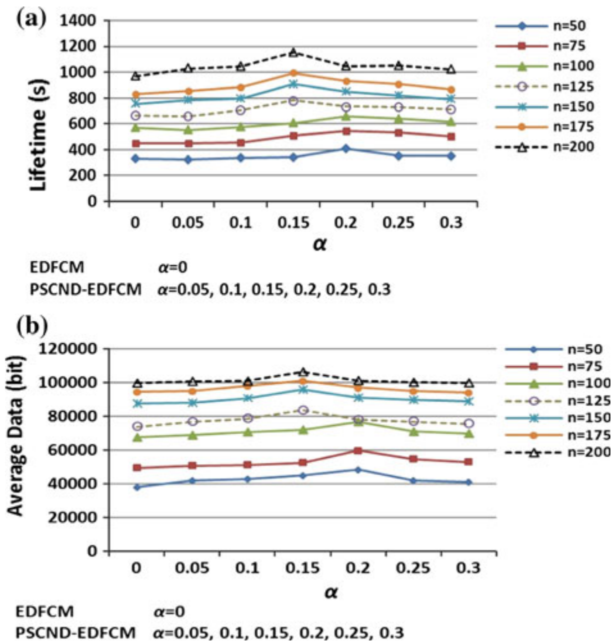


Fig. 6 Comparing of EDFCM and PSCND-EDFCM. **a** Network lifetimes. **b** Data transmission

PSCND-DEEC is proposed for the heterogeneous networks (with similar feature as DEEC). The PSCND-DEEC protocol considers some other parameters such as the α parameter, the nodes' location, and CHs' positions in addition to the nodes residual energies and the network average. The new CHs selection threshold is calculated by Eq. (19). The results indicate that PSCND-DEEC have the maximum network lifetime and data transmission for $N = 50, 75,$ and 100 at $\alpha = 0.2$; and in high dense networks, i.e. $N = 125, 150, 175,$ and 200. The network lifetime and data transmission diagrams slowly grow when the α value increases from $\alpha = 0$ up to $\alpha = 0.15$ and achieve their maximum points when $\alpha = 0.15$.

Figures 6a, b show the results of the applying PSCND model in EDFCM protocol for the network lifetime and data transmission respectively, with different α values and node numbers.

PSCND-EDFCM, like EDFCM protocol, is based on the method of energy dissipation forecast and clustering management. They consider the residual energy and energy consumption rates in all nodes for selecting proper CHs. PSCND-EDFCM surveys the CHs' positions in each round and selects the CHs by using the CHs selection threshold of Eq. (28). Results indicate that PSCND-EDFCM have the maximum network lifetime and data transmission for low dense networks with $N = 50, 75,$ and 100 when $\alpha = 0.2$, and also in higher density networks with $N = 125, 150, 175,$ and 200 the maximum performances are achieved for $\alpha = 0.15$.

As expected, the network lifetime and data transmission increase when node densities are high. Furthermore, effectiveness of the PSCND method depends tightly on the α values. When $\alpha = 0$, it does not affect on clustering process of LEACH, DEEC and EDFCM protocols, whereas for $\alpha > 0$ the cluster process is affected by α values precisely. Figures 4, 5 and 6 detect the optimal α values for various densities. Also network lifetime and data transmission

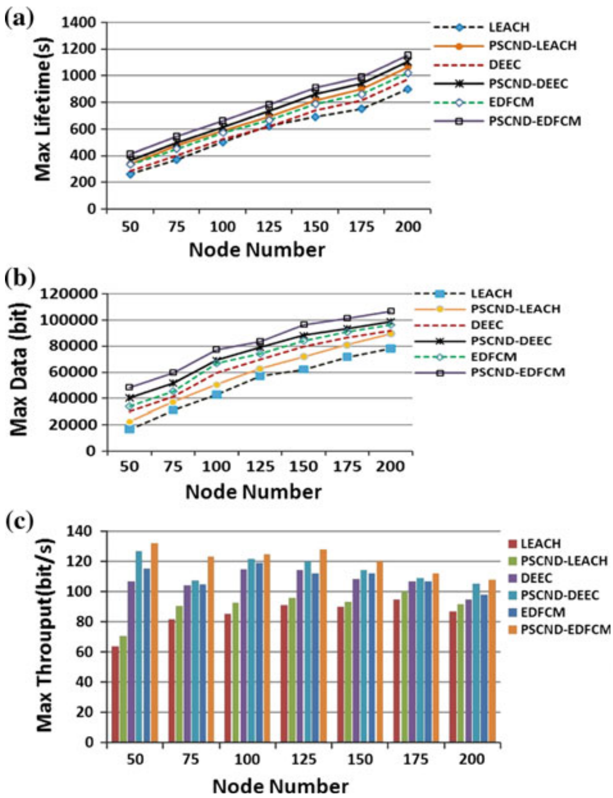


Fig. 7 **a** The maximum network lifetime. **b** The maximum data transmission. **c** The maximum network throughput

slightly increase till they meet the optimal α value, and afterward they decrease again. It should be noted that by getting closer to the optimal value α the network performance improves. From the results in Figs. 4, 5 and 6, it can be concluded that the high dense networks have long lifetime and hence more data transmission. As a result, applying PSCND in the cluster-based routing protocols increases 15 % of network lifetime and the average data transmission improves 14 % in all three discussed protocols.

Actually, achieving an optimal α value is one of the important goals of the simulation. The diagrams depicted in Fig. 7 are based on the maximum amounts of the network lifetime and the data transmission which are extracted from Figs. 4 and 5 in the optimum α values. So, Fig. 7a–c indicate that these parameters improve in the homogeneous and heterogeneous networks by increasing the node density.

To evaluate the network performance, the network throughput or digital bandwidth consumption is computed by dividing the number of data packets to time to get it in bit per second, in other words the amount of data delivered to the BS is divided by network lifetime [55,57]. The diagrams depicted in Fig. 7c are based on the amounts of the network lifetime and data transmission which are obtained from Figs. 4, 5 and 6. As mentioned above, the PSCND method can be applied in both homogeneous and heterogeneous networks. In homogenous cluster-based routing protocols like LEACH and PSCND-LEACH, network throughput increases by increasing the nodes densities. Because the increasing rate of data transmission in high dense networks is higher than increasing rate of the network lifetime, so network throughput increases by density increments in homogenous networks. But in heterogeneous protocols with different types of initial energy of nodes (E_0 for the normal nodes and E_0 $(1 + \beta)$ for the advanced ones), the low-energy nodes will die more quickly than the high-energy ones, and new nodes can be replaced with dead ones which generate the heterogeneity in terms of energy and prolongs network lifetime. In network with long lifetime, more data are transmitted and network throughput increases with low slope, especially in high dense networks. Therefore, it can be concluded that LEACH throughput is increased in high node numbers due to its homogeneity, but throughput of DEEC and EDFCM slightly decreased with increasing node numbers because of their heterogeneity.

5 Conclusions

In this paper, a heuristic method of clustering (PSCND) is proposed for homogenous and heterogeneous WSNs. The selection of CHs in PSCND is modeled as FLP that is solved by linear programming model to guarantee an optimal solution. This mechanism seeks to provide an efficient method for optimal CHs distribution in network throughout and creates networks with maximum coverage and minimum cluster overlapping in order to improve network performance. Employing PSCND model in cluster-based routing protocols not only does not change the energy distribution model and the protocols' criteria, but also adds some parameters such as the α parameter, nodes' locations and the CHs distances from each other, to select the optimal CHs and to overcome the challenges in this issue. Results of simulation showed that the indicator function presented by FLP, increases network efficiency by an optimum value of α obtained from simulation results in different network densities. Results also indicate that applying PSCND in cluster-based routing protocols prolongs 15 % of the network lifetime, increases 14 % of data transmission and improves 5.5 % of throughput, as compared to the results of current heuristic methods such as LEACH, DEEC, and EDFCM protocols. In addition, it is observed that PSCND can improve network scalability and outperforms in high dense networks. But considering the overhead added by high ratio of transmitted neighbor discovery control packet in high dense network motivated us for further study on wake/sleep scheduling. It is expected that using wake/sleep schedules in high dense networks may help overcome the reverse effect of inappropriate α values on the network performance, which in turn leads to energy saving.

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