Low Energy Adaptive Clustering in Wireless Sensor Network Based on Spectral Clustering

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***Abstract*— Wireless Sensor Networks (WSNs) are composed of large number of sensor nodes that are randomly distributed in a region of interest. The nodes are responsible of the supervision of a physical phenomenon and periodic transmission of results to the sink. Energy saving results in extending the life of the network, which presents a great challenge of WSNs. This paper focuses primordially on reducing the power consumption of WSN. To deal with this, a hierarchical clustering scheme, called Multi-Relay K-way Spectral Clustering Algorithm (MR-KSCA), is proposed. This algorithm is based on spectral classification and graph theory with the aim to cluster the network in a fixed optimal number of clusters. Thus, our approach ensures an ideal distribution of sensor nodes in clusters, and proposes new features to elect the appropriate cluster-heads, which guarantee an uniform distribution load of energy among all the sensor nodes. Furthermore, We present three metrics to define the WSN lifetime. In term of extending the network lifetime and minimizing the energy consumption, the simulation results show an important improvement on the network performances with MR-KSCA compared to other existing clustering methods.**

Keywords-Wireless Sensor Network; Clustering; Graph theory; Spectral classification; Energy consumption.

I. INTRODUCTION

A Wireless Sensor Network (WSN) is a wireless network consisting of spatially distributed autonomous devices using sensors to cooperatively monitor physical or environmental conditions at different locations, such as temperature, sound, and vibration. It contains a large number of nodes, which sense data from an inaccessible area and send their reports towards a processing center called Base Station (BS) or Sink. WSNs have many advantages, such as the ease deployment and the capacity of self-organization. However, their main challenges are the limited resources in terms of radio communication capabilities and energies. This article addresses this last point. it is based on [1] that was presented in SENSORCOMM 2013.

WSN has been widely used in many areas especially for surveillance and monitoring in agriculture and habitat monitoring. Environment monitoring has become an important field of control and protection, providing real time system and control communication with the physical world [2]. In this paper, we propose an energy efficient cluster based routing algorithm for environmental monitoring system.

Even if the sensors are usually powered by batteries, it is not practical to recharge or replace them, because they are often deployed in hostile environments. Furthermore, in a WSN, a large part of energy is consumed when communications are established [3]. Hence, frequent and long distance transmissions should be minimized to extend the lifetime of the network. One way to reach this result consists in dividing the network into multiple clusters; each cluster has a cluster-head (C-H) [4]. The C-H node collects data from nodes of its same cluster, aggregates them and transmits them to the BS. Nevertheless, the main problem of many proposed clustering protocols is the random selection of the C-H nodes [5]. Indeed, all C-Hs can be located in a small region of the network, and some ordinary nodes will be isolated. Also, the nature of the clustering problem is such that the ideal approach is equivalent to finding the global solution of a non linear optimization problem. This is usually a difficult task to achieve. In actual fact, this is an NP-hard problem [6]. To tackle the clustering problem and to fairly localize C-H nodes, we propose to consider spectral clustering methods and the sensor's residual energies.

Spectral clustering has become one of the most popular modern clustering algorithms. It is based on graph theory, can be solved efficiently by standard linear algebra software. It also outperforms traditional clustering algorithms such as the k-means algorithm [7]. Spectral clustering is refereed to a class of techniques, which rely on the eigen-structure of a similarity matrix to partition points into disjoint clusters (i.e., points in the same clusters have high similarity and points in different clusters have low similarity [8]. These spectral clustering algorithms have attracted attention over the past few years in many applications, such as image segmentation [9] and social network analysis [10]. The K-way approach is one of these methods. It consists to divide points into K disjoint classes. This method is based on the K eigenvectors related to the K largest eigenvalues of Laplacian matrix [11].

Following this approach, we present a Multi-Relay K-way Spectral Clustering Algorithm (MR-KSCA) in Wireless Sensor Networks. MR-KSCA consists in partitioning the Wireless Sensor Network into a set of clusters based on spectral classification. Besides, it determines the C-H nodes and super cluster-head node (super C-H) based on the residual energy of each node of the network. Some other properties will be explained in Section IV.

Thus, MR-KSCA has four main goals: (i) extending the network lifetime by distributing energy consumption, (ii) running the clustering process within a constant number of iterations/steps, (iii) minimizing control overhead (to be linear in the number of nodes), and (iv) producing well-distributed C-Hs and compact clusters. MR-KSCA does not make any assumptions about the distribution or density of nodes, neither about node capabilities.

We test the proposed algorithm through simulations and compare the results with other clustering algorithms. Results show that our proposed method is far better than the others With respect to energy consumption and network lifetime.

The remaining of this paper is organized as follows: In Section II, we give a brief overview of some related research work. Section III describes the network model and states the addressed problem in this work. Details and properties of the proposed algorithm are given in Section IV while Section V presents the simulations and the results. Finally, conclusion and some perspectives are drawn in Section VI.

II. RELATED WORK

Many routing protocols have been designed based on clustering [5][12][13], While there are advantages to use distributed cluster formation algorithms, these protocols offers no guarantee about the placement and the number of the C-H nodes. However, using a central control algorithm to form the clusters may produce better clusters by dispersing the C-H nodes throughout the network. This is the basis of our proposed algorithm.

Moreover, the most commonly used approach for clustering is the Low-Energy Adaptive Clustering Hierarchy (LEACH) algorithm [14]. LEACH is an energy-efficient communication protocol, which employs a hierarchical clustering. Besides, many clustering protocols based on the principle of this algorithm have been developed, such as LEACH-Centralized (LEACH) [15], Energy-Kmeans [16], DECSA [17], EECS [18] and SECA [19].

In LEACH, nodes organize themselves into clusters using a distributed algorithm. Its main idea is to randomly and periodically select the C-H nodes. The probability of becoming a C-H for each round is chosen to ensure that every node becomes a C-H at least once within N/K rounds, where N is the number of nodes in the network and K is the desired number of clusters. Thus, In order to select C-H nodes, each node i determines a random number between 0 and 1 if the number is less than threshold $T(i)$, the node becomes a C-H for the current round. The threshold is set as follows:

$$T(i) = \begin{cases} \frac{K}{N-K*\left(r*mod\left(\frac{N}{K}\right)\right)} & : \quad C(i)=1 \\ 0 & : \quad C(i)=0 \end{cases} \tag{1}$$

$C(i)$ is the indicator function determining whether or not node i has been a C-H in the most recent $\left(r * mod\left(\frac{N}{K}\right)\right)$ rounds (i.e., $C(i) = 1$ if node i has been C-H and zero otherwise). After the election of C-H nodes, each ordinary node in the wireless sensor network determines its cluster by choosing the C-H that requires the minimum communication energy, based on the received signal strength of the advertisement from each C-H. Each ordinary node will choose to join the C-H which has the highest signal quality. Once the clusters are formed, each C-H node creates Time Division Multiple Access (TDMA) schedule. The C-H collects and aggregates information from sensors in its own cluster and passes on information to the BS. Although LEACH distributed clustering algorithm has advantages, using a central control algorithm to form clusters may produce better clusters by dispersing the C-H nodes throughout the network [14].

In LEACH-Centralized (LEACH-C), also described in [15], uses a centralized algorithm to form clusters. The BS determines the C-H nodes by computing the average node energy. The node with energy below this average can not be C-Hs for the current considered round. This ensures that the energy consumption will be effectively distributed among all the nodes.

Yong and Pei [17] present a Distance-Energy Cluster Structure Algorithm (DECSA) based on the classic clustering algorithm LEACH. This proposed approach considers both the distance between the nodes, the position of the base and residual energy of nodes. Its main idea is to partition the network into three levels of hierarchy to reduce the energy consumption of the C-H nodes. This results from the non-uniform distribution of nodes in the network and thus avoid direct communications between BS and C-H node that has minimal energy and is far away from the BS.

Elbhiri et al. [20] propose a new approach called the Spectral Classification based on Near Optimal Clustering in Wireless Sensor Networks. This approach is based on spectral bi-section for partitioning a sensor network into two clusters. Spectral bi-section method is based on second eigenvalue λ_2 of the Laplacian matrix of the graph to be partitioned. Median value of corresponding eigenvector of λ_2 is used to bi-part the graph [11]. The authors apply this method recursively to obtain the desired number of clusters. Then, for each cluster, a C-H is also elected. This task is assigned by rotating way between nodes without considering the residual energy of the nodes. Hence, this method cannot partition the network into any desired number of clusters and do not ensure an equitable distribution of energy consumption between sensor nodes.

III. RADIO MODEL AND PROBLEM STATEMENT

This paper discusses the periodical data gathering application [21], for which LEACH is proposed. Thus, the proposed clustering algorithms usually produce clusters of the same size. The C-H node consumes the same amount of energy during intra-cluster communications. Moreover, C-H election method based essentially on residual energy can obtain better energy efficiency than the method in which cluster heads are elected in turns or by probabilities. For this, we use the spectral classification that is widely used to solve graph partitioning problems. The spectral methods get their name from the spectral theories of linear algebra. This theories allows affirming the diagonalization of real symmetric matrices. It also justifies the decomposition of real symmetric matrices into eigenvalues in an orthonormal set of eigenvectors. Besides, the graph partitioning problem can be reduced to the resolution of a numerical system $Mx = \lambda x$. Solving this numerical system consists in seeking an orthogonal base of eigenvectors of the matrix M [11].

In our approach, the BS constructs the graph corresponding to the WSN based on the spectral clustering principle. Let x be an observation vector composed of the sensor network nodes. This vector can be represented by an undirected graph $G(V, E)$; where V is the set of vertices (sensor nodes) identified by an index $i \in \{1, \cdots, N\}$ (let N be the number of nodes) and E is the set of edges that link each two vertices (communication link). Let $A \in \Re^{N\times N}$ be the similarity matrix of the graph G. Each value of A is associated to each pair of the graph nodes (i, j). The total weight of incident edges to node i is given by $d_{ii} = \sum_{j=1}^{j=N} a_{ij}$. The degree matrix $D \in \Re^{N\times N}$ of G is a diagonal matrix defined by $D = [d_{ij}]$. Finally, the Laplacian matrix of the graph, as illustrated by [11], is expressed as follows :

$$L = D^{-\frac{1}{2}} \ * A \ * D^{-\frac{1}{2}} \tag{2}$$

To simplify the network model, we make some assumptions that are:

- All nodes are homogeneous and have the same capacities.
- Each node is assigned a unique identifier (id) that includes the cluster identifier to which the node belongs.
- The network topology remains unchanged over time.
- The BS is placed far away from the network.

In addition, we use the model of the radio hardware energy dissipation presented in [14][15], as illustrated in Figure 1. In this model, the multipath fading channel is used when the distance between the sender and the receiver is more than threshold d_0; otherwise the free space model is used. Therefore, in order to transmit an $L - bits$ message with

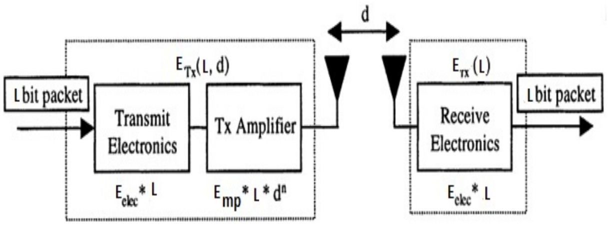


Fig. 1. Radio energy dissipation model.

distance d there would be:

$$E_{Tx}(L, d) = \begin{cases} L \ * E_{elec} + L \ * E_{fs} \ * d^2 & if \ d < d_0 \\ L \ * E_{elec} + L \ * E_{mp} \ * d^4 & if \ d \geq d_0 \end{cases} \tag{3}$$

To receive this message, the required amount of energy would be:

$$E_{Rx}(L, d) = L \ * E_{elec} \tag{4}$$

where E_{elec} is the energy consumption per bit in the transmitter and receiver circuitry, E_{fs} or E_{mp} is the energy dissipated per bit to run the transmit amplifier. The threshold's value (d_0) is expressed as follows:

$$d_0 = \sqrt{\frac{E_{fs}}{E_{mp}}} \tag{5}$$

IV. MR-KSCA Details

In this section, we give details of the proposed MR-KSCA algorithm (Figure 2). MR-KSCA considers the following clustering model: The sensor nodes are divided into several clusters by using spectral clustering method. For each resulting cluster, one sensor node is selected as a cluster-head. Then, from this set of C-H nodes, one node is selected as super C-H node. This super C-H node plays the role of virtual BS. Thus, the C-H nodes collect data from other sensor nodes in the cluster and transfer the aggregated data to the super C-H node or the BS, and the super C-H node collect data from the C-H nodes and transfer the aggregated data to the BS. Therefore, the data which are collected by the cluster head far away from the BS must be forwarded by the other C-H nodes that are close to the BS. Since data transfers to the BS dissipate much energy, the nodes take turns with the transmission: the role of cluster-head and super cluster-head "rotate". This rotation leads to a balanced energy consumption of all nodes and hence to a longer lifetime of the network. Some other properties and details will be explained in the subsections.

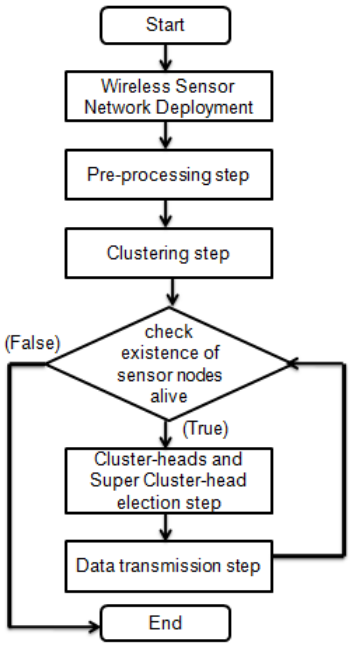


Fig. 2. Flowchart of the proposed algorithm.

The spectral classification algorithm proposed here consists of three steps, as illustrated in Figure 3.

A. The Pre-Processing step

First, each sensor node determines its position by using a number of different technologies, e.g. exploiting radio or

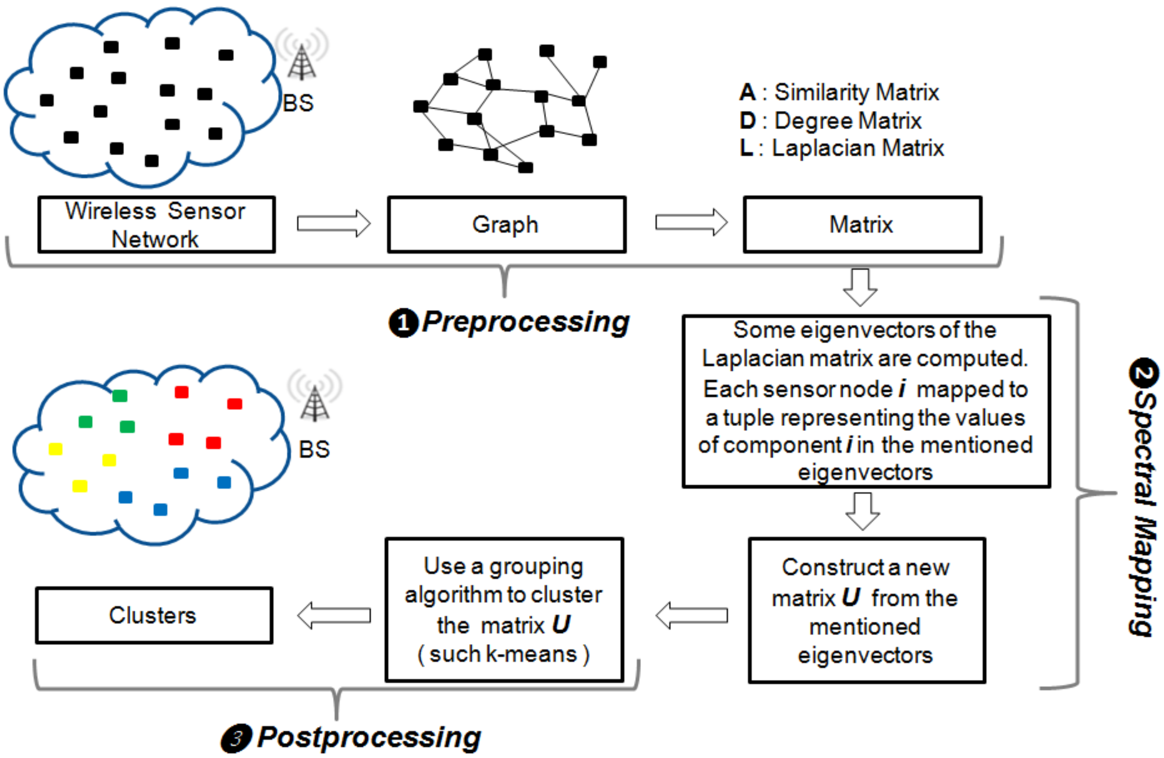


Fig. 3. Spectral clustering scheme of the MR-KSCA approach.

sound waves [22]. After that, it transmits the derived position to the BS in a short message. Based on the spectral clustering principle, the BS constructs the graph G and the similarity matrix A which represents the network. There are several popular constructions to transform a given set of data points with pairwise similarities into a graph. When constructing similarity graphs the goal is to model the local neighborhood relationships between the data points [7]. Here we simply connect all points with positive similarity with each other, and we weight all edges by a_{ij}. In our approach we consider the similarity function as a Gaussian similarity function. Hence, similariy matrix is constructed as follows:

$$A = [a_{ij}] = \begin{cases} exp\left(\frac{-1}{2\sigma^2} * d^2(i,j)\right) & if\ i \neq j \\ 0 & otherwise \end{cases} \quad (6)$$

with $d(i,j)$ is the Euclidean distance between nodes i and j. It should be noted that a_{ij} is large when points indexed by i and j are likely to be in the same cluster.

Thereafter, the BS must deduce the Degree Matrix and the Laplacian one. Then, it computes the eigenvalues and the eigenvectors of the last matrix.

B. Clustering step

The objectives of the current step are to define the optimal number of clusters and to form them.

As indicated in [15], the optimal number of clusters can be determined as follows:

$$K = \frac{\sqrt{N}}{\sqrt{2\pi}} * \sqrt{\frac{E_{fs}}{E_{ms}}} * \frac{M}{d^2_{toBS}} \quad (7)$$

where N is the number of sensor nodes, M is the area of sensor nodes deployment, and d_{toBS} is the average distance of the nodes from the BS.

We construct a new matrix U from the K eigenvectors related to the K largest eigenvalues of the Laplacian matrix. In order to determine the K clusters of the WSN, we apply the classification algorithm k-means to the matrix U. We deal with each row of U as a point in $\Re^{K\times N}$. We cluster the WSN into K clusters via k-means. The sensor node i is assigned to cluster C_j if and only if row i of the matrix U was assigned to cluster C_j.

We notice that in the proposed algorithm we determine the clusters before specifying the C-Hs and the optimal number of clusters is as well defined automatically. So, our algorithm is different from the others (such as LEACH, LEACH-C, DECSA, etc.) that determine the C-H nodes before the clusters. In addition, in order to define the number of cluster heads, the latter protocols run the same technique in each iteration and by the way consume more energy.

C. Cluster head election step

Once the clusters are determined, the next step of the MR-KSCA consists to select the C-H nodes. The C-H nodes are responsible of the coordination among the nodes within their clusters, as well as for the aggregation of the received information and the communication with the BS or the super C-H node. In our algorithm, the C-H is determined by taking into account the id of the node in the cluster and its residual energy (Algorithm 1). The id is defined without considering the position of the node in the cluster. The C-H in each round of communication will be at a random position on the cluster. Thus, the probability of uncovered area will decrease extremely.

Indeed, for each round r of the simulation, we use the number $C_k = (r \ mod \, |S_k|)$ to elect a C-H for the appropriate cluster; $|S_k|$ is the total number of nodes in the cluster k. The node with $id = C_k$ and residual energy E_r greater than threshold E_{rmin} will be the C-H of the cluster k in the round r. E_{rmin} is the minimum residual energy required for a given node to be a C-H. It is the summation of the energy needed to receive and process data coming from the appropriate cluster nodes (data aggregation), and to transmit data towards the BS. This energy E_{rmin} is given by:

$$E_{rmin} = |S_k| \ * (E_{Rx}\,(L, d) + E_{Aggregation}) + E_{Tx}\,(L, d) \tag{8}$$

with

- $E_{Tx}\,(L, d)$is the energy consumed when the C-H transmits $L - bits$ data to the BS by a distance d.
- $E_{Aggregation}$ is the energy needed by the C-H to process data:
$$E_{Aggregation} = L \ * E_{DA} \tag{9}$$
E_{DA} is amount of energy for data aggregation.
- $E_{Rx}\,(L, d)$is the energy consumed when the C-H receives data from one node.

Hence,

$$E_{rmin} = L * \big((|S_k| + 1) \ * E_{elec} + |S_k| \ * E_{DA} + \epsilon_{mp} \ * d_i^4\big) \tag{10}$$

Nevertheless, if the residual energy E_r is less than E_{rmin} this node must broadcast a short message informing the node with $id = C_k + 1$to its residual energy and so on. Thus, the energy consumption will be distributed with more equitable between all nodes.

Algorithm 1 Cluster Head Election

- **For** each round r
  - **For** each cluster k in $\{1, 2, \cdots, K\}$
    - $*$ Each node i of the cluster k with the id in $\{1, 2, \cdots, |S_k|\}$ computes the value $id_{CH} = (r \ mod \, |S_k|)$
    - $*$ **While** $E_r(id_{C-H}) \leq E_{rmin}$
      - $\cdot$ $id_{C-H} = id_{C-H} + 1$

      End While
    - $*$ Node with $id = id_{C-H}$ will be the C-H for the current round r

    End For

  End For

D. Super cluster head election step

This step consists of selecting the super C-H node from the set of C-H nodes. In our approach, the ordinary nodes report their data to the respective C-H nodes. The C-H nodes aggregate the data and send them to the BS through the super C-H node. If the C-H nodes transmit data over longer distance to reach the BS directly, they lose more energy compared to ordinary nodes. Hence, the super C-H node play the role of the second BS. We also assume that if the distance between the C-H node and the BS is lower than the distance between the C-H node and the super C-H node. Then, the C-H node transmits its data directly to the BS.

Thus, in our algorithm the super C-H is determined by taking into account the residual energy of the nodes. The super cluster head will be the C-H with the highest level of the residual energy.

E. Data Transmission

Based on the id and the numbers of nodes in the cluster, the C-H node creates a schedule TDMA to assign to each member's node a time when it can transmit its data to its own C-H. If we suppose that the node with the $id = i$ is elected as a C-H, the node with $id = ((i + 1 + |S_k|) \ mod \, |S_k|)$ is assigned the first round to transmit its data.

One of the most important challenges in our approach consists in reducing the total consumed energy of each round. Hence, we avoid energy consumption due to synchronization of the cluster nodes when the C-H is elected to assign the TDMA. Indeed, this technique ensures not having collisions between data messages. It also allows the radio components of each non-C-H node to be disabled at any time, except during the time it is allocated for transmitting these data. this reduces the energy consumed by the nodes. However, the C-H must keep its receiver "ON" in order to receive data from other nodes [23]. In addition, to save more energy in a WSN, we assume that if the distance between a node and the BS is lower than the distance between this node and its C-H. Then the node transmits its data directly to the BS. Moreover, each node can move in the standby mode to reduce energy consumption.

Also, to avoid unnecessary node s control messages transmission and control overhead of the BS, the clusters are created only when the sensor nodes are deployed in the first round. So, the calculating overhead is only C-H selecting and super C-H selecting in the most set-up phase.

V. Simulations and Results

In this section, we present the results of the evaluation experiments of the proposed MR-KSCA algorithm. We used the MATLAB software to simulate and analyze this algorithm. Besides, we consider the radio model presented in Figure 1. The different parameters used in our simulations are shown in Table I.

A node that runs out of energy is considered dead and cannot transmit or receive data. For these simulations, the energy of a node decreases each time it sends, receives or aggregates data according to the model radio parameters. Also, we ignore the effect caused by the signal collision and the interference in the wireless channel. Furthermore, each simulation result shown below is the average of 100 independent experiments,

Algorithm 2 Data Transmission

- **For** each round r
  - **For** each cluster k in $\{1, 2, \cdots, K\}$
    - ∗ The C-H node creates Time-Slot assignment TDMA.
    - ∗ The C-H node collects measurement from cluster's nodes.
    - ∗ **If** the distance between C-H and BS is lower than the distance between C-H and super C-H
      - · The C-H node sends aggregated data to the BS.

      Else
      - · The C-H node sends aggregated data to the super C-H node.

      End If

  End For

End For

TABLE I. EXPERIMENTAL SIMULATION PARAMETERS.

Parameter	value
E_{elec}	$50nJ/bit$
E_{fs}	$10pJ/bit/m^2$
E_{mp}	$0.0013pJ/bit/m^4$
Initial energy E_0	$0.5J$
E_{DA}	$5nJ/bit/message$
Area of Network	200m ×200m
Sink coordination	$(100m, 250m)$
d_0	$88m$
Message Size	$4000bytes$
Number of Nodes	500

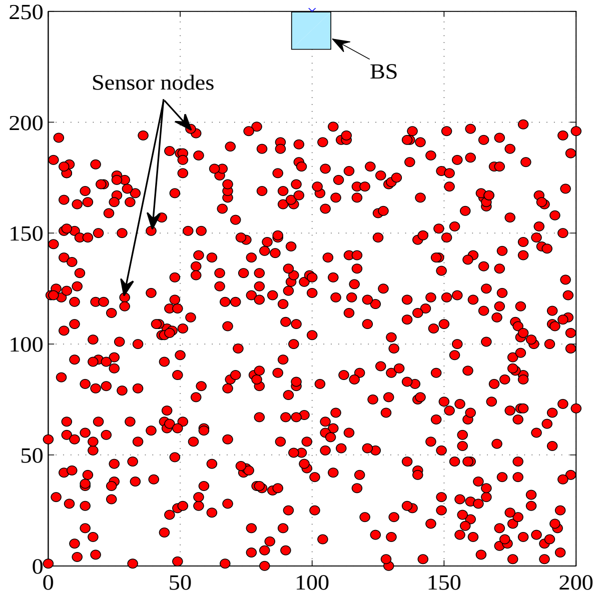


Fig. 4. Random deployment of 100 nodes over an area of size 200m ×200m.

where each experiment uses a different randomly-generated uniform topology of sensor nodes.

As illustrated in Figure 4, an example of WSNs with $N = 500$ nodes randomly distributed in a 200m ×200m area. The BS is located far away from the sensing area ($x_{SB} = 100m$; $y_{SB} = 250m$).

In order to evaluate the performances of the new proposed protocol, we propose to compare it to:

- K-way Spectral Clustering Algorithm (KSCA) [1].
- Spectral Classification based on Near Optimal Clustering (SCNOC) [20].
- Distance-Energy Cluster Structure Algorithm (DECSA) [17].
- Low Energy Adaptive Clustering Hierarchy Centralized (LEACH-C) [15].

Also, we use two metrics to analyze and compare the performances of the protocols:

- **Network lifetime:** It is necessary that all nodes stay alive as long as possible. Network quality decreases considerably as soon as one node dies. Thus, it is important to know when the First Node Died. Furthermore, sensors can be placed in proximity to each other. Thus, adjacent sensors could record related or identical data. Hence, the loss of a single or few nodes does not automatically diminish the quality of service (QOS) of the network. In this case, the metric **First Node Died** (FND) denotes the time elapsed until first node depletes its energy. The metric **Half of the Nodes Died** (HND) denotes the time elapsed until half of the nodes in the network are dead. Finally, the metric **Last Node Died** (LND) gives an estimated value for the overall lifetime of a sensor network.
- **Energy consumption:** Uniform energy consumption is very important for network load balancing: More uniform energy consumption, less possibility for node premature death. Less energy consumption per round, better network performance.

As illustrated in Figure 5, the main problem of LEACH-C and DECSA protocols are the random selection of the C-H nodes. It is obvious that a stochastic C-Hs selection will not automatically lead to minimum energy consumption during data transfer for a given set of nodes. All C-H nodes can be located near the edges of the network or adjacent nodes can become C-Hs simultaneously. In these cases some nodes have to bridge long distances to reach a C-H.

In SCNOC algorithm, when we use only the second eigen-

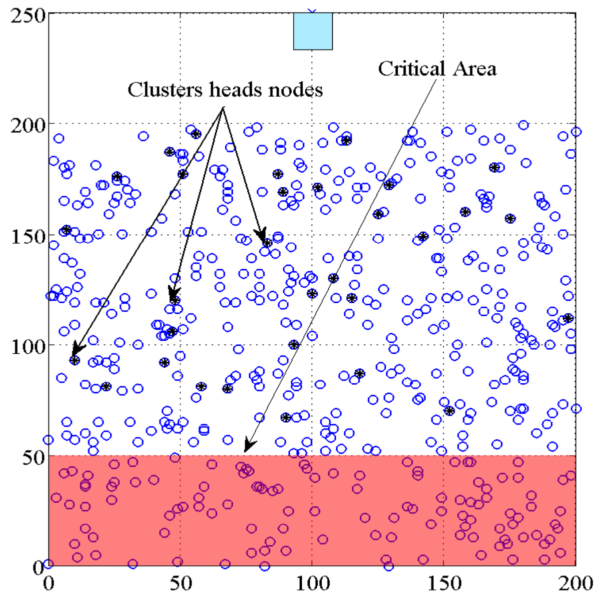


Fig. 5. Illustration of the critical area in the LEACH-C clustering algorithm with 500 nodes.

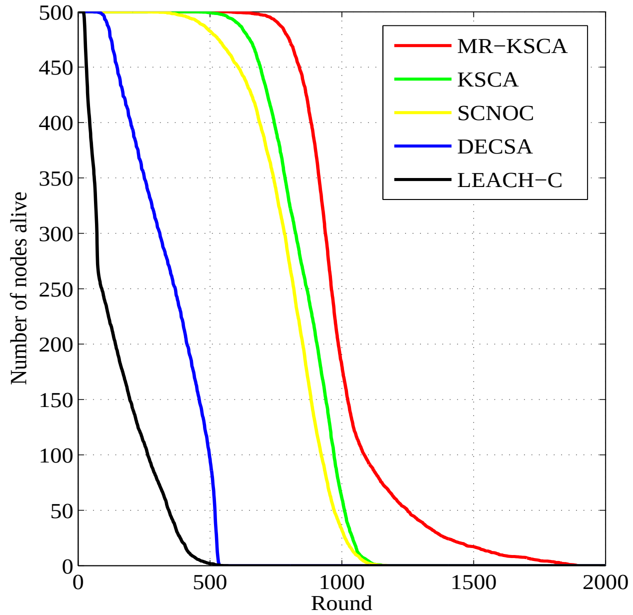


Fig. 7. Number of nodes alive over time of the compared protocols.

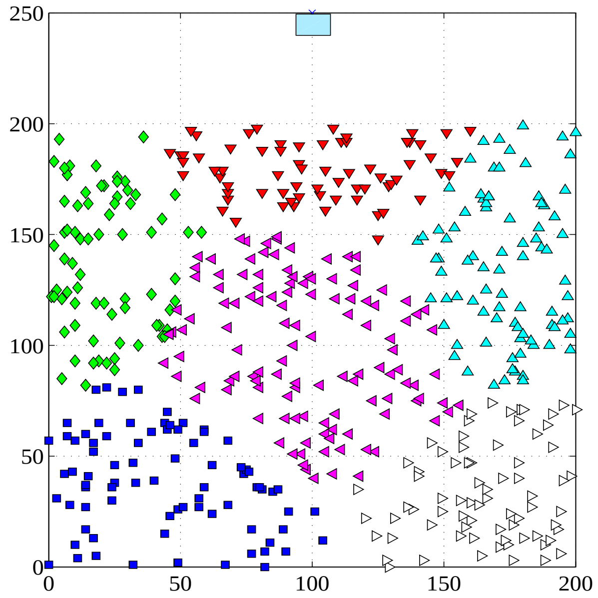


Fig. 6. Clustering results of the MR-KSCA algorithm with 500 nodes.

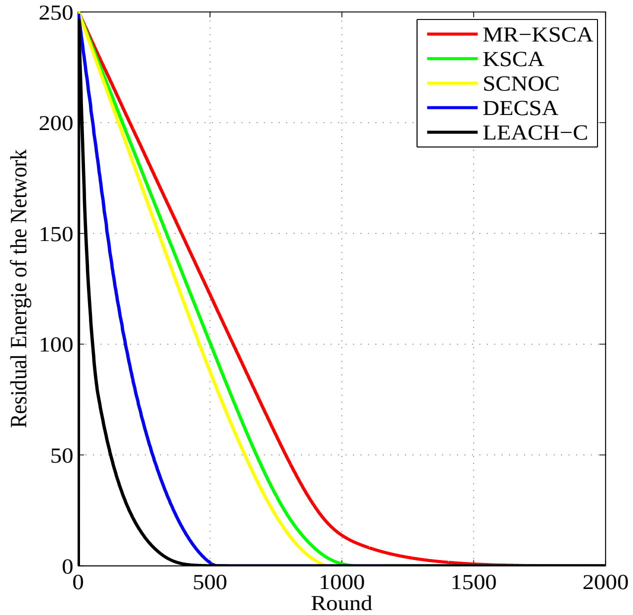
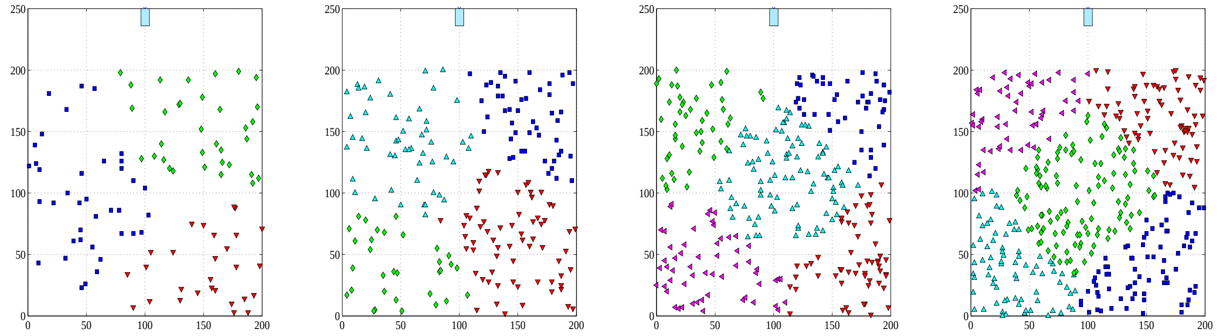


Fig. 8. Evolution of the remaining energy in the network when the transmission rounds.

vector of the Laplacian matrix in the clustering setup, we may lose the connectivity information about the network [11] and obtain a poor clustering setup.Also, we cannot partition the network into the optimal number of clusters. On the other hand, the rotation selection of the C-H nodes may obtain a poor C-H selection setup, the distribution of C-H nodes is not uniform and some sensor nodes have to transfer data through a longer distance. Hence, reasonable energy saving is not obtained.

In KSCA, all C-H nodes transfer their data directly to the BS. Hence, some C-Hs which are far away from the BS consume exhaustive energy.

Figure 6 presents an example of clustering setup for the MR-KSCA. We note that the network is subdivided into



(a) N=100 (b) N=200 (c) N=300 (d) N=400

Fig. 9. Clustering results of MR-KSCA algorithm for different number of nodes.

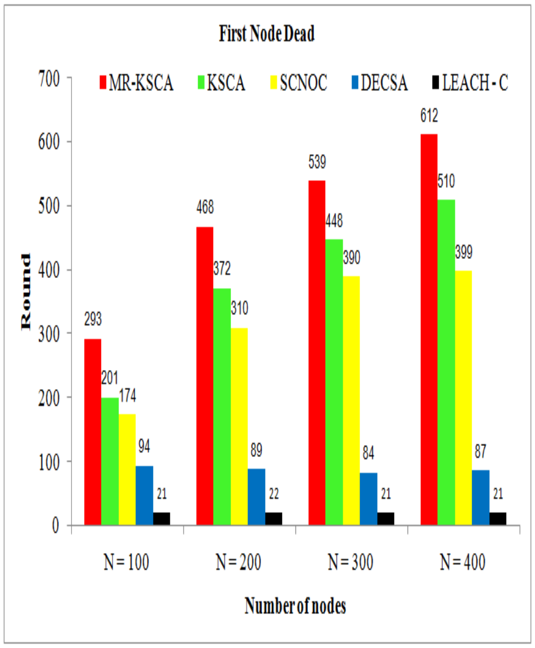


Fig. 10. Impact of the node density on the ”First Node Died”.

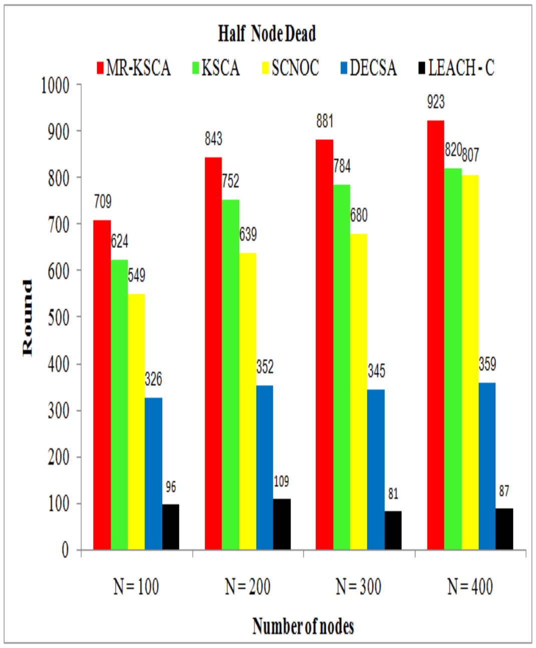


Fig. 11. Impact of the node density on the ”Half Node Died”

six clusters, and the nodes are correctly distributed over the sensing area. Also, there is no intersection between the different clusters.

Figure 7 shows a significant improvement for MR-KSCA in terms of numbers of periods relating to FND, HND, and LND. In the proposed method, FND occurs at the round 641 while it occurs at the round 520 for KSCA, at the round 378 for SCNOC, at the round 21 for LEACH-C, and at the round 74 for DECSA protocols. HND occurs at the round 960 while it occurs at the round 867 for KSCA, at the round 817 for SCNOC, at the round 89 for LEACH-C, and at the round 368 for DECSA protocols. Finally, LND occurs at the round 1865 while it occurs at the round 1171 for KSCA, at the round 1080 for SCNOC, at the round 568 for LEACH-C, and at 541 for DECSA protocols.

Figure 8 gives the total network energy remaining in every transmission round. The energy remaining decreases more rapidly in KSCA, SCNOC, LEACH-C, and DECSA than in MR-KSCA. In the first 500 transmission rounds, approximately 51.3% of the total energy is consumed in case of MR-KSCA. Whereas, 60% in KSCA, 65% in SCNOC, 98% in DECSA, and 100% in LEACH-C.

Figure 9 presents the clustering setup for different number of nodes. In each case, we note that the network is subdivided into an optimal number of clusters. There is no intersection between the different clusters. Also, the C-H nodes will be distributed over the sensing area.

In Figures 10-12, we show the effects of the node density on the compared clustering techniques as well as on the network's stable regions (”FND”, ”HND”, ”LND”). For different values of N equal to 100, 200, 300, and 400, our algorithm presents an improvement of performances compared to the other algorithms. It follows that even if the node density increase the new proposed approach still gives best results compared to the

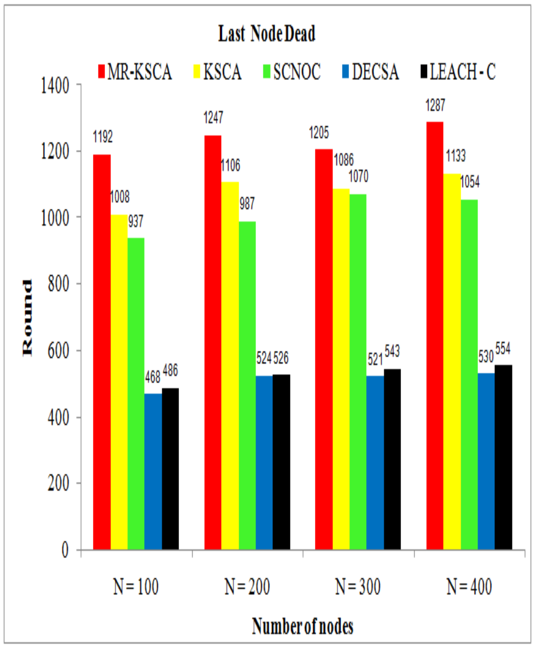


Fig. 12. Impact of the node density on the "Last Node Died"

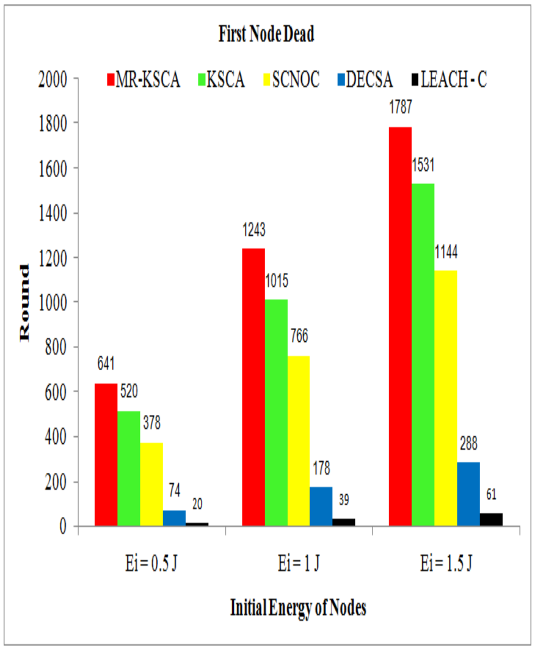


Fig. 13. Impact of the initial energy quantity on the "First Node Died".

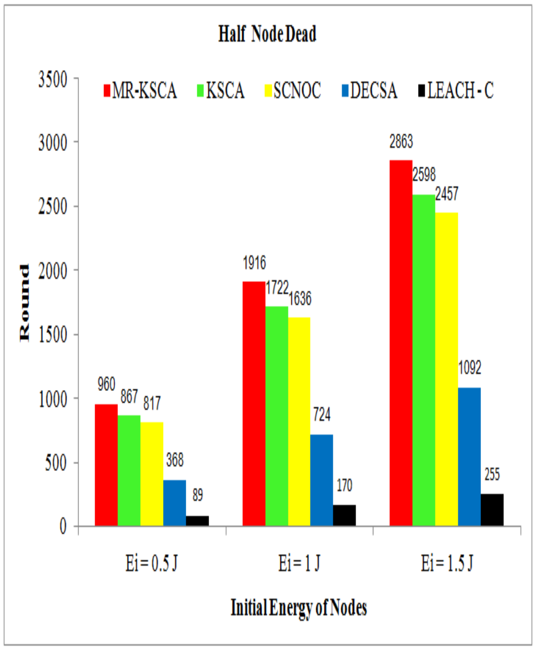


Fig. 14. Impact of the initial energy quantity on the "Half Node Died".

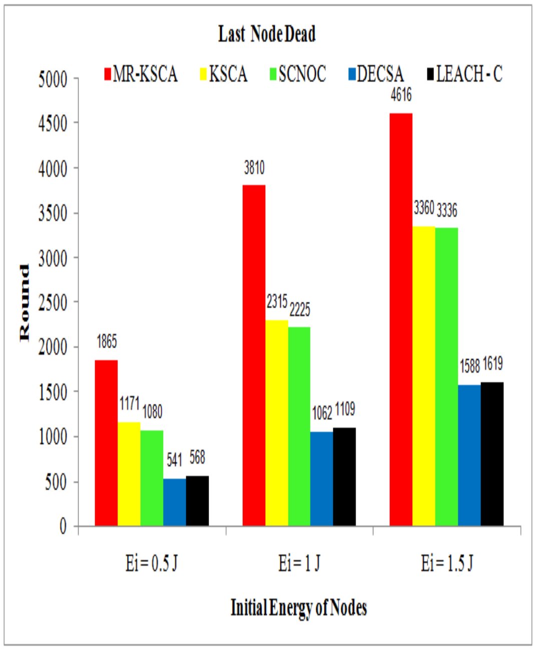


Fig. 15. Impact of the initial energy quantity on the "Last Node Died".

other ones.

In Figures 13-15, we show the performances of the different compared protocols by using different initial energies. It gives respectively the "FND", "HND", and "LND" depending on the quantity of the nodes initial energy.

Once more, it is shown that for different values of the energy, the new proposed approach presents a significant improvement compared to the others. We conclude that the MR-KSCA algorithm gives a significant performance improvement; in terms of energy and lifetime gains, compared to the KSCA, the SCNOC, the LEACH-C, and the DECSA protocols. The best results of the MR-KSCA approach can be explained by the three points: (i) The proposal starts by selecting the clusters (similar nodes) before the election of the C-Hs. (ii) The approach considers the residual energies of the nodes when we select the C-H nodes. (iii) The C-H nodes are distributed in the WSN.

VI. Conclusion and future work

Energy saving is an important challenging issue in a WSN. To ensure more effective energy distribution and extend the lifetime of the network, energy-efficient saving scheme is developed in this paper. We have proposed a new method of clustering (MR-KSCA), based on spectral classification (K-way) that has been widely used to solve graph partitioning problem. Our approach starts by determining similar nodes (clusters) and after that, selects C-H nodes. Furthermore, MR-KSCA considers the energy of the nodes when selecting C-H nodes and the super C-H node, so the nodes with more energy have more chance to be the C-Hs or super C-H. Hence, balancing energy consumption is guaranted. Indeed, simulation results show that our approach ensures the low energy consumption and improves the network lifetime. Further directions of this study will be deal with clustered sensor networks with more than two levels of hierarchy and more than three types of nodes.

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