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Energy optimization in wireless sensor networks using a hybrid K-means PSO clustering algorithm

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Abstract: Energy saving in wireless sensor networks (WSNs) is a critical problem for diversity of applications. Data aggregation between sensor nodes is huge unless a suitable sensor data flow management is adopted. Clustering the sensor nodes is considered an effective solution to this problem. Each cluster should have a controller denoted as a cluster head (CH) and a number of nodes located within its supervision area. Clustering demonstrated an effective result in forming the network into a linked hierarchy. Thus, balancing the load distribution in WSNs to make efficient use of the available energy sources and reducing the traffic transmission can be achieved. In solving this problem we need to find the optimal distribution of sensors and CHs; thus, we can increase the network lifetime while minimizing the energy consumption. In this paper, we propose our initial idea on providing a hybrid clustering algorithm based on K-means clustering and particle swarm optimization (PSO); named KPSO to achieve efficient energy management of WSNs. Our KPSO algorithm is compared with traditional clustering techniques such as the low energy adaptive clustering hierarchy (LEACH) protocol and K-means clustering separately.

Key words: Wireless sensor network, clustering algorithms, k-means, particle swarm optimization

1. Introduction

A wireless sensor network (WSN) is a network with a collection of sensor nodes communicating with each other using radio signals with the objective to sense, monitor, and explain some phenomena. WSNs have found many applications in industry, science, health care, transportation, civil infrastructure, and security. They were used in diverse applications including habitat and environmental monitoring [1], visual surveillance for automatic object detection such as real-time traffic monitoring and vehicle parking control [2], intrusion detection [3], and noise pollution monitoring [4]. WSNs suffer many challenges. Some of these challenges include network protocol [5], coverage problems [6], data gathering and distribution [7], time constraints [8], energy management [9–11], fault detection [12], and security [13]. A typical WSN consists of number of sensor nodes (i.e. nodes) [14]. The number of sensor nodes could be from a few nodes up to several thousand based on the size of the coverage area. Each node is normally connected with other nodes in the network so that they can exchange data about various events that could happen in an environment. Each node normally consists of several components such as a radio transceiver and microcontroller. An electronic circuit is also part of the sensor node [15]. This circuit is responsible for managing the energy source during deployment and transmission.

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A WSN is similar to any network with an adopted topology. Some examples of the WSN topologies are the star network and the multihop wireless mesh network. The propagation technique for data flow between the nodes could be routing or flooding [16]. A survey of the state-of-the-art routing techniques in WSNs can be found in [17]. An example of WSN architecture can be seen in Figure 1. The main components of a WSN were described in [18].

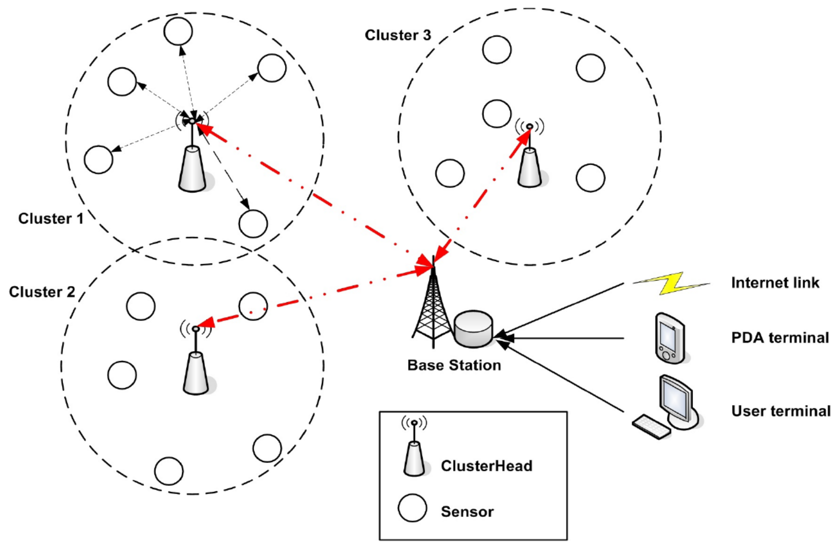

Figure 1. A wireless sensor network architecture [18].

This paper is organized as follows: in Section 2, we introduce the concept of clustering in WSNs. In Section 3, we provide a brief description of the LEACH protocol. A basic introduction to the K-means clustering algorithm is stated in Section 4. A detailed explanation of the advantages of PSO and how they work to solve nonlinear parameter optimization problems is provided in Section 5. The proposed hierarchical K-means PSO clustering algorithm is presented in Section 6. The results and analysis of our proposed algorithm are presented in Section 7. We finally provide our conclusion and expected future work.

2. Clustering for WSNs

Clustering has been extensively studied in the data processing and network literature [19–21]. It is capable of enhancing the network lifetime, which is an essential attribute for assessing the quality of a sensor network. Maximizing the static network lifetime of wireless ad hoc networks was extensively studied [22]. One of the network lifetime definitions is 'the duration of time until the first node failure due to battery depletion' [23]. Others define it as the time at which a fraction of nodes die [24]. Clustering in a WSN involves grouping nodes into clusters and choosing a CH. The CH is responsible for collecting data from sensor nodes in its group and sending the gathered data to the sink (i.e. base station).

The sensors in a cluster connect with their CH directly. The CH sends the gathered data to the sink. Clustering has many advantages such as grouping sensors and saving energy losses. These advantages can be summarized as follows [25]:

- Communicate collected data to the base station.
- Reduce the number of nodes responsible for sending data.
- Increase energy saving.
- Allow scalability by increasing the number of nodes.
- Reduce communication overhead.
- Provide a better use of network resources.

3. What is the LEACH clustering protocol?

The LEACH protocol is one of the well-known WSN clustering protocols [26]. It elects the CH based on a probability distribution function. The LEACH protocol repeats a two-phase round: a setup phase and steady-state phase. CH election is done periodically and in a randomized manner during the setup phase. The steady-state phase is divided into a number of frames. Each frame is divided equally into slots, one for each live node. During each frame, every sensor node sends the data to its CH, and then the CH sends the gathered data to the base station. With this approach, LEACH claims to balance energy consumption of the sensor nodes. However, it does not guarantee good distribution or uniform representation of the cluster heads. In spite of its nonuniformity in CH representation, LEACH is considered a testing benchmark for most WSN clustering algorithms.

4. What is K-means clustering?

K-means is known to be an unsupervised clustering algorithm. It was successfully used to solve a variety of clustering problems. It was applied to partition a network into a number of clusters [27–29]. The algorithm can mainly partition the space of nodes into k clusters based on the distance between an elected CH and the rest of the nodes in the same cluster.

The K-means clustering algorithm is shown in Figure 2. This algorithm aims at minimizing an objective function, in this case a squared error function. The objective function is given in Eq. (1).

$$J=\sum_{j=1}^{k}\sum_{i=1}^{n}||S_i^j-CH_j||^2 \tag{1}$$

Here, $||S_i^j-CH_j||$ is a chosen distance measure between a sensor S number i belonging to cluster j and the CH for n sensors.

5. What is PSO?

In 1995 Kennedy and Eberhart [30] introduced a robust stochastic nonlinear optimization technique based on movement and intelligence of swarms, named PSO. PSO was inspired by the social behavior of birds, where a group of birds constitute a swarm. The birds randomly search for food by following the nearest bird to the food. PSO combines local search methods with global search methods, and it depends on social interaction within the swarm to locate the best achieved position so far. The main idea of PSO is obtaining a number of particles that move around in the search space and communicate with their neighborhood to locate the best solution. The choice of the neighborhood to communicate with, named the swarm topology, affects the model used in the implementation. Two famous topologies are:

- Star topology: all particles in the swarm communicate with each other.
- Ring topology: each particle communicates with only two neighborhoods.

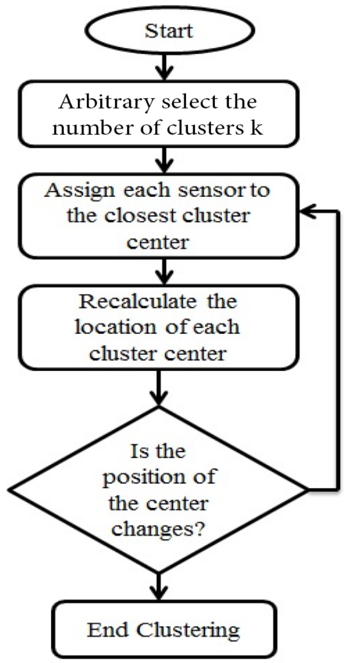

Figure 2. A flow chart for the K-means clustering algorithm.

Star topology has the advantage of fast convergence. However, this fast convergence is misleading in some cases, where premature convergence is reached. Ring topology is characterized by having slower and less premature convergence and it performs better on multimodal problems. Different topologies were proposed and discussed in [31,32]. In implementations of PSO, each particle modifies its position using information such as its current position, its current velocity, the distance between the current position and best solution individually found, and the distance between the current position and the best solution found by its neighborhood [33]. Depending on the problem to be solved, a fitness function is used to assess the quality of the PSO solution. The PSO equations are given as follows:

$$v_{id}^{new}=v_{id}^{old}+\psi_1*\alpha_1*(p_{id}-x_{id})+\psi_2*\alpha_2*(p_{gd}-x_{id}) \tag{2}$$

$$x_{id}^{new}=x_{id}^{old}+v_{id}^{new} \tag{3}$$

where:

v_{id} represents the velocity of particle i in dimension d,

x_{id} represents the position of particle i in dimension d,

$\psi_1\psi_2$ are positive constants,

$\alpha_1\alpha_2$ are random numbers

p_{id} is the best position reached so far by the particle, and

p_{gd} is the global best position reached by the neighborhood.

The velocity of PSO should not exceed a maximum value, v_{max}, to avoid an unstable state. The performance of PSO search can suffer if the maximum velocity is inappropriately set. If it is too high, the particles can fly past optimal solutions, and if it is too low they can get stuck in local minima. Other models of the velocity equation were shown in [34] and [35].

The PSO algorithm is straightforward (see Algorithm 1). First, initialize particles with random position and velocity vectors. For each particle: evaluate the fitness and if it is better than the best individual fitness then update it. After that, update the best global fitness. Then obtain the new velocity and position for each particle. This procedure is repeated for a number of iterations or until convergence is beyond a certain limit.

6. Proposed hybrid K-means PSO clustering algorithm

In the past, PSO was applied to obtain the optimum cluster layout using various fitness functions [36–38]. PSO was also embedded in another algorithm to solve the WSN clustering problem as in [39]. Although it produces promising results, developing a low computational and high performance clustering algorithm is still a challenge.

Algorithm 1. Basic steps describing the PSO algorithm.

---

begin PSO

Randomly initialize the position and velocity of the particles: $X_i(0) and V_i(0)$

while (While terminating condition is not reached) do

for for i = 1 to number of particles

Evaluate the fitness:$= f(X_i)$

Update $p_i and g_i$

Update velocity of the particle V_i

Update position of the particle X_i

Evaluate the population.

Next for

end while

end PSO

The main objective of our proposed WSN clustering algorithm is to group the sensor nodes into a number of clusters. To partition n nodes into k clusters, an exhaustive algorithm has to go through $2^n - 1$ solutions to find the optimal clustering layout. Solving such problem is known to be NP-hard. We propose a hybrid K-means PSO clustering algorithm (KPSO) to solve the energy consumption problem based on clustering. Figure 3 shows the phases of our proposed mechanism.

- Phase 1: The first phase applies the K-means algorithm to partition the network into k clusters.
- Phase 2: Next, the PSO algorithm searches for the best CH within each cluster obtained by the K-means.
- Phase 3: Finally, the last stage evaluates the obtained cluster layout.

With our proposed hybrid algorithm, the clustering problem will be easily managed with less computation required. By using our proposed algorithm for partitioning, the search space will be reduced to about $\frac{n}{k}$ solutions for each cluster.

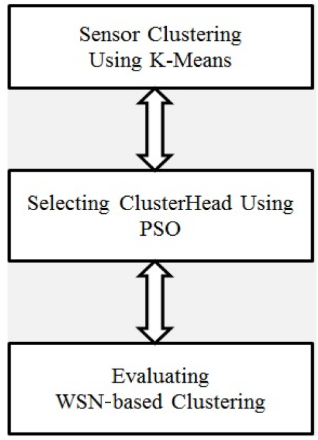

Figure 3. Hybrid K-means PSO clustering algorithm.

6.1. Phase 1: clustering-based K-means

In our proposed algorithm, the K-means clustering algorithm is applied to partition the network into an arbitrary selected number of clusters. The base station will select k nodes as CHs, and then each node joins its nearest CH. A new CH is chosen as the middle of the cluster. These steps are repeated until no new CH is selected. The distance between two nodes s_1 and s_2 is computed based on the following Euclidean distance calculation:

$$Distance(s_1 s_2) = \sqrt{(x_{s1} - x_{s2})^2 + (y_{s1} - y_{s2})^2} \tag{4}$$

where x and y are the node's x-coordinate and y-coordinate, respectively. This phase will divide the network into disjoint clusters. The base station will save information about each cluster's sensor ID and location.

6.2. Phase 2: cluster head selection using PSO

The PSO algorithm is then applied to select the optimal cluster head from each cluster obtained by the K-means phase. For instance, if the K-means algorithm partitioned z nodes to 3 clusters with l, m, and n nodes, respectively, then the PSO model will select three cluster heads: one from the l nodes, the second from the m nodes, and the third from the n nodes. PSO will search the space of all possible CHs that save energy and provide a convergence to the best solution. Many evaluation criteria can be adopted to find the best CH.

For partitioning z nodes into k clusters, the particle structure will be an array containing the indices that represent a possible node selected from each cluster to be its CH, as shown in Table 1. The size of the PSO particle is fixed, consisting of k entries, where k is the number of WSN clusters.

Table 1. PSO particle structure.

CH_1	CH_2	......	CH_k

6.3. Phase 3: cluster layout evaluation

Our proposed fitness function is given in Eq. (5). It represents an indicator of the number of transmissions a CH can perform during its lifetime. E_i represents the CH's actual energy and d_i is the Euclidean distance between the cluster head and the base station. The value of d_o is 87 m [26]. The objective of the PSO algorithm is to maximize the fitness function in order to achieve the maximum lifetime of the cluster head.

$$F=\begin{cases} \sum_{i=1}^{allCHs} \frac{E_i}{d_i^2} & for d_i<d_0 \\ \\ \sum_{i=1}^{allCHs} \frac{E_i}{d_i^4} & for d_i\geq d_0 \end{cases} \tag{5}$$

Here we show the equations adopted to calculate the energy consumed in transmitting a 1-bit message over short and long distances, respectively. The energy consumed by a CH is given in Eq. (6), while Eq. (7) shows the energy consumed by a non-CH node.

- n_i is the number of nodes belonging to CH$_i$.
- d_{toBS} is the Euclidean distance between the CH and the base station.
- d_{toCH} is the Euclidean distance between the node and its CH.
- E$_e$ = 50nj, E$_{DA}$ = 5nj, ε_s = 10pj/m^2, and ε_l = 0:0013pj/m^4.

$$DE_{CH_i}=\begin{cases} n_iE_e+n_iE_{DA}+\varepsilon_s d_{toBS}^2 & for d_i<d_0 \\ n_iE_e+n_iE_{DA}+\varepsilon_l d_{toBS}^4 & for d_i\geq d_0 \end{cases} \tag{6}$$

$$DE_{nonCH_i}=\begin{cases} E_e+\varepsilon_s d_{toCH}^2 & for d_i<d_0 \\ E_e+\varepsilon_l d_{toCH}^4 & for d_i\geq d_0 \end{cases} \tag{7}$$

6.4. Developed WSN clustering toolbox

A WSN clustering tool is implemented to develop and simulate our proposed algorithm. The proposed MATLAB toolbox consists of the following components:

- WSN Data Component for entering the sensor nodes and base station data.
- Clustering Component that runs our KPSO algorithm.
- Simulator Component for evaluating the performance of the WSN cluster layout resulting from the clustering component.

In Figure 4, we show the graphical user interface (GUI) of the developed toolbox implemented by the MATLAB program. The WSN Data Component is for statically entering the simulation parameters of the geographic data, the base station location and the number of sensor nodes. The nodes' location can be randomly generated, loaded from a MATLAB workspace, or entered manually.

The toolbox adopted the fitness function presented in Eq. (5) as the default choice. Other fitness functions, such as the total clustered distance, may be also selected. The GUI allows the user to observe the K-means clustering layout (the left graph), our proposed KPSO clustering algorithm layout (middle graph), and the PSO fitness conversion (on the right). The developed toolbox then triggers our developed simulator to run the evaluation task. The simulator component calculates the total consumed energy and the number of live nodes based on the radio model described in [40]. The results are shown in another GUI window given in Figure 5. The graph on the left shows the simulated total remaining energy of the generated cluster layout. The other graph shows the total number of live nodes.

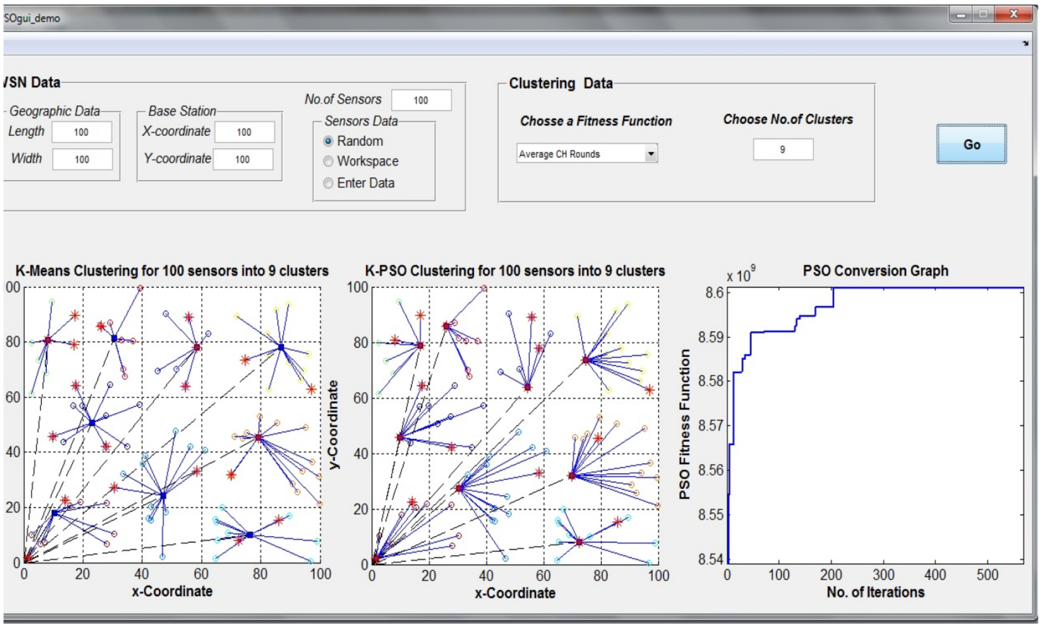

Figure 4. GUI showing the (a) K-means clustering distribution, (b) KPSO clustering distribution, and (c) convergence curve of the KPSO algorithm.

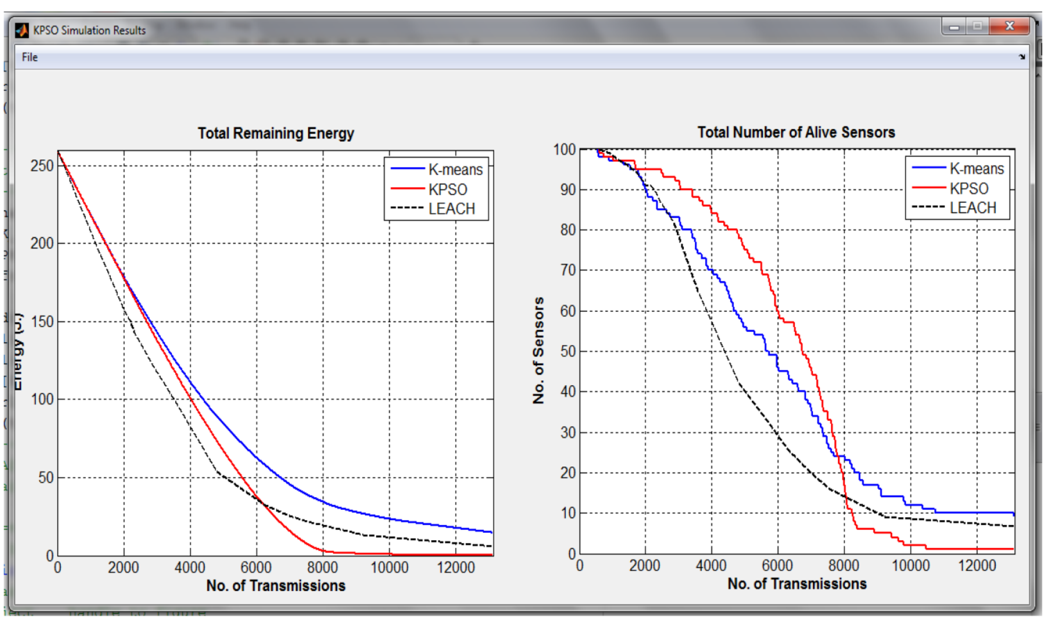

Figure 5. GUI simulation showing the total remaining energy and the total number of live sensors for the three algorithms.

6.5. Proposed simulation environment

For proper operation of our proposed algorithm, some assumptions were made. We assume a fixed number of static nodes that are randomly deployed in a two-dimensional geographical area. The nodes are assumed to have an initial energy level. The base station has no constraints on its energy and computing resources. It has an updated record of each node's location. We assume that the communication is established over time. Within each cluster, each pair of sensor nodes is guaranteed to be within the effective transmission range so each two nodes in the cluster can communicate with each other directly. Table 2 lists the values of the parameters adopted in our experiment.

Table 2. WSN simulation parameters.

Parameter	Value
Field size	100 *times* 100 m^2
Number of sensors	100
Energy of sensors	80% of sensors have 2 J, 20% of sensors have 5 J
Base station location	(0,0)

Computation of the number of clusters: a pretest is made to discover the number of clusters that produces the minimum communication distance. Figure 6 shows the total communication distance versus the number of clusters. Nine clusters are chosen to be used in our KPSO algorithm test.

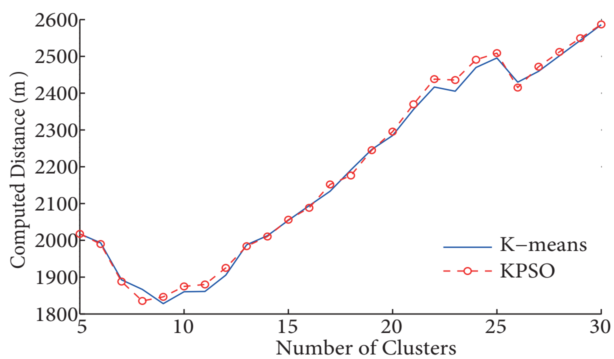

Figure 6. Communication distance vs. number of clusters.

PSO model used: For the PSO phase, the time-varying acceleration coefficient PSO model is implemented [35]. The acceleration coefficients ψ_1 and ψ_2 vary with time. At earlier stages, the algorithm gives more weight to the cognitive component in order to explore the search space thoroughly. At later stages the social component focuses on the promising region to get the best result. Table 3 lists the parameters of the PSO model used. Figure 7 shows the fitness conversion curves with various numbers of particles. In our case, 20, 40, 60, and 80 PSO particles were used, respectively.

Table 3. PSO simulation parameters.

Parameter	Value
Inertia weight	From 0.9 to 0.1
ψ_1	From 2.5 5 to 0.5
ψ_2	From 0.5 5 to 2.5
No. of particles	20, 40, 60, and 80

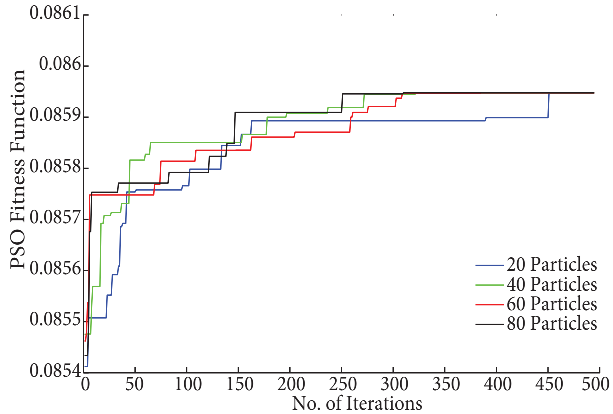

Figure 7. PSO fitness function conversion.

7. Simulation results and analysis

In this section, our proposed algorithm (KPSO) is evaluated and compared with two clustering algorithms. They are the K-means algorithm and the LEACH protocol. The developed toolbox was used over a number of experiments with various layouts in order to test our proposed algorithm efficiently. Now we report our results based on each phase of our proposed hybrid algorithm.

Developed cluster layout: The developed cluster layout of the K-means algorithm, the layout after applying our KPSO algorithm, and the cluster layout formed by the LEACH protocol are presented in Figure 8. The nodes marked with red stars are those having high energy. The LEACH distribution shows a higher number of randomly chosen clusters. The cluster head selected from our KPSO algorithm is not necessarily the center of the cluster as selected by K-means algorithm. Our KPSO algorithm selects the cluster head that can survive for a maximum number of transmissions.

7.1. Comments on energy computation

In this section, we discuss some observations of our developed results. It is essential to increase the network lifetime by managing the network remaining energy and the total number of live sensors during the simulation. The total remaining energy based on the three algorithms studied in this research (i.e. K-means, LEACH protocol, and our KPSO algorithm) are presented in Figure 9.

In a transmission cycle, each node sends a single data message to its CH. Then the CH aggregates the received data into one message. Finally, the CH sends the aggregated message to the base station. Figure 10 shows the number of live nodes versus the number of transmissions. We concluded the following facts:

- The LEACH protocol consumes the highest energy among the three algorithms.
- The K-means algorithm consumes less energy than our KPSO algorithm because its cluster head is the center of the cluster, leading to minimum communication distance.
- The CH as presented in our proposed KPSO algorithm is not always the center of the cluster. Thus, the communication distance is greater than or equal to that of the K-means communication distance in some cases.
- Our proposed KPSO algorithm has a longer lifetime compared to the K-means algorithm. The reason is our adopted fitness has the advantages of considering both the node's actual energy and the communication distance at the same time.

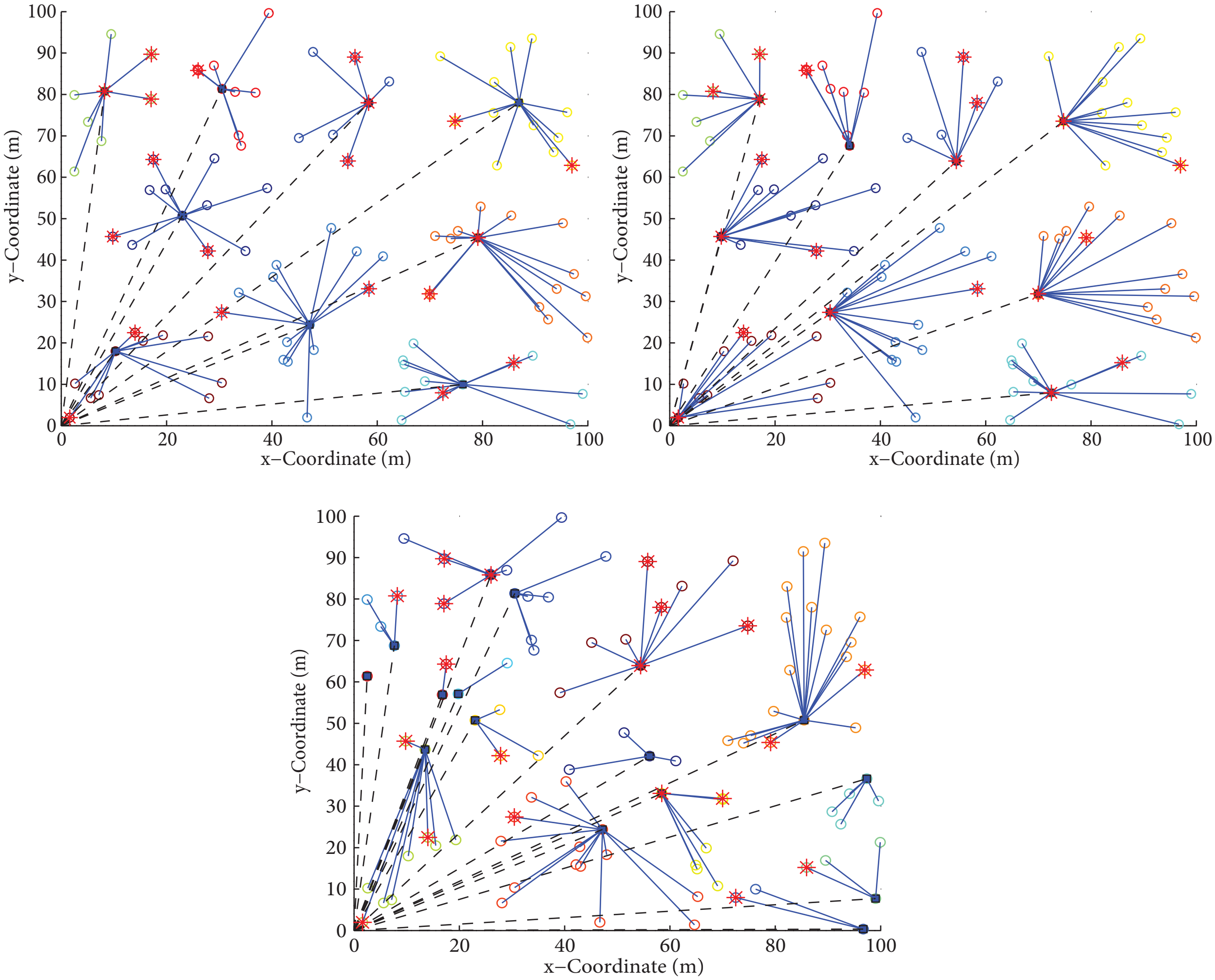

Figure 8. (a) K-means clusters, (b) KPSO clusters, (c) LEACH clusters.

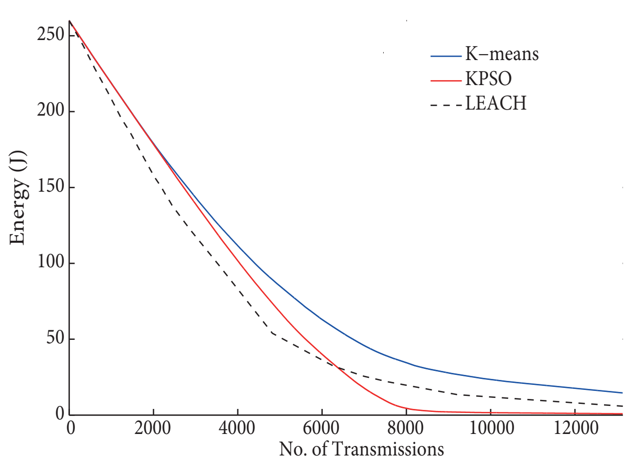

Figure 9. Total remaining energy vs. number of transmissions.

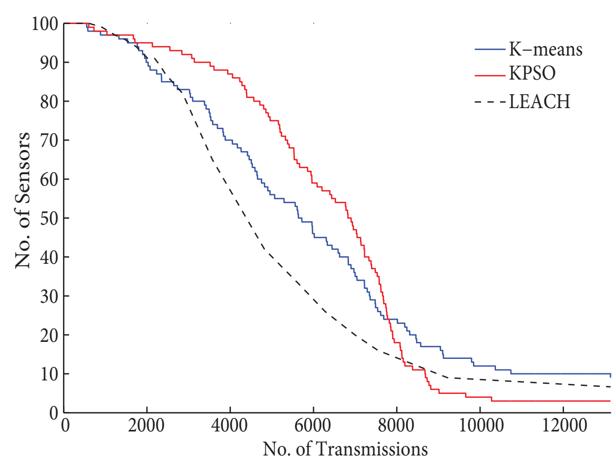

Figure 10. Total number of live sensor nodes vs. number of transmissions.

- Our proposed algorithm shows a higher number of live nodes than the other two algorithms. To show how we made the comparison, we considered a threshold of 30% of the total WSN nodes as a guide for comparison. Above this level our algorithm performs better than the K-means algorithm and LEACH protocol.

Table 4 shows the simulated number of transmissions performed by the network given that a fixed number of nodes are live. Figure 11 shows the percentage improvement of the KPSO transmissions over the K-means algorithm and LEACH protocol. The percentage improvement over LEACH is calculated based on the following equation:

$$\text{Improvement}=\frac{KPSO_{Rounds}-LEACH_{Rounds}}{LEACH_{Rounds}}*100\% \tag{8}$$

Table 4. Simulated number of transmissions.

Number of Alive Sensors	Simulated transmissions		
	K-means	LEACH	KPSO
100	555	610	604
90	2031	2183	3518
80	3384	2858	4714
70	4054	2858	5377
60	4753	3572	5963
50	5722	3572	6905
40	6835	4822	7333
30	7361	5655	7679
20	8460	6994	7903
10	13,133	7549	8690

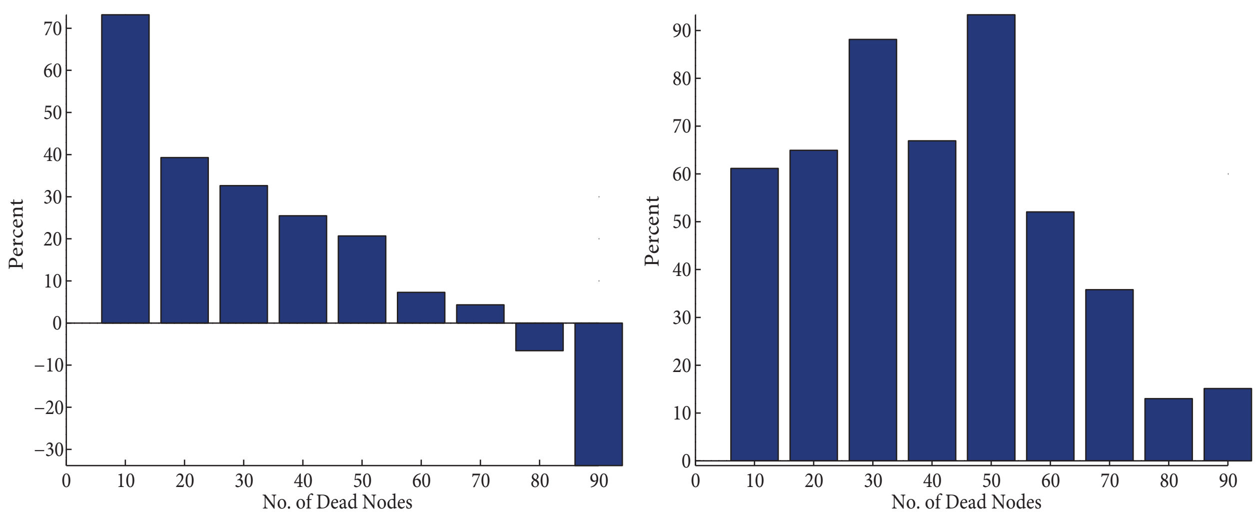

Figure 11. Percentage improvement in the KPSO algorithm compared to (a) K-means and (b) LEACH.

7.1.1. Variation of number of sensor nodes

Network layouts with different numbers of sensors are examined to evaluate our KPSO algorithm. Two network layouts were explored in our study. The base station location was arbitrarily fixed at point (0,0). Figure 12 shows the number of live nodes for the two network layouts having total number of nodes equal to 200 and

400, respectively. The two networks are assumed to be in the same geographic area of 100 m $\times$ ~100 m. We assumed that 80% of the nodes have 2 J energy, while the rest of the nodes have 5 J energy.

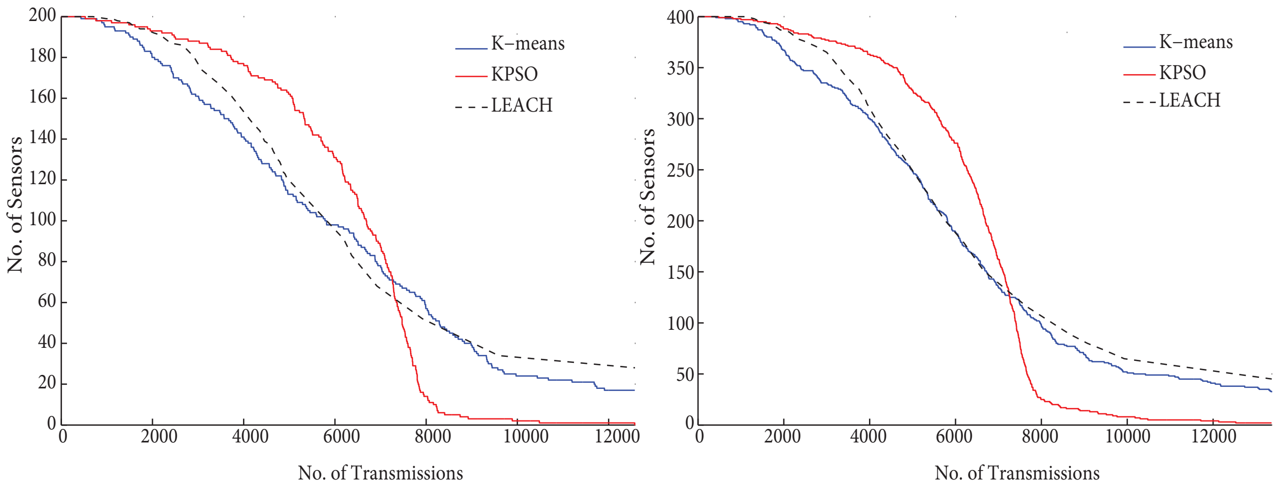

Figure 12. (a) Total number of live sensor nodes for 200 sensors; (b) total number of live sensor nodes for 400 sensors.

Table 5 lists the average improvement in the KPSO performance compared to the LEACH algorithm. The results show that our KPSO algorithm performs more transmissions than the LEACH protocol when the number of live nodes in the network is more than 30% of the total nodes in the network. The performance improvement of KPSO over K-means is almost not affected by the number of sensors.

Table 5. Average performance improvement.

No. of sensors	Average improvement in the no. of transmissions (%)	
	Improvement over LEACH	Improvement over K-means
100	48.9473%	17.1305%
200	9.9840%	20.2557%
400	9.0727%	19.5852%

7.1.2. Variation of energy of sensor nodes

Varying the node's energy is always essential for WSN performance and it affects the network lifetime. That is why we decided to explore the effect of having sensors with various energy distributions on the three algorithms. We adopted an arbitrary layout that has 100 sensors distributed in a geographic area of 100 m $\times$ 100 m and a base station at point (0,0). Three situations were considered. They are:

- Case 1: all sensor nodes have the same energy of 2 J.
- Case 2: 80% of the sensor nodes have 2 J and 20% of sensor nodes have 5 J.
- Case 3: 50% of the sensor nodes have 2 J and the other 50% have 5 J.

Studying Case 1 and Case 3, our proposed algorithm performs slightly better than the other two algorithms. In Case 2, our KPSO algorithm outperforms both the K-means algorithm and the LEACH protocol. This is more likely to be the case in practice. There is no guarantee that all the sensors will have the same energy distribution in the field. Figure 13 show the performance graph of the adopted algorithms according to the node's energies. The lists of the average improvement of KPSO compared to both the K-means algorithm and the LEACH protocol is presented in Table 6.

Table 6. Average performance improvement.

Energy of sensors	Average improvement in the no. of transmissions (%)	
	Improvement over K-means	Improvement over LEACH
2 J each	8.0251%	4.5850%
80% have 2 J and 20% have 5 J	17.1305%	48.9473%
50% have 2 J and 50% have 5 J	9.0486%	7.4124%

7.1.3. Variation of the base station location

The location of the base station is an essential element that can affect the WSN operation lifetime. To study its effect, we have arbitrarily chosen two different locations for a base station simulation. They are the point (50,50) and the point (50,175) in the work environment. The results show that the network performs better when the base station is located away from, or at the corner of, the nodes' geographical area. The performance is simulated as shown in Figure 14. Our KPSO algorithm was able to select the CHs that perform more transmissions based on the fitness criteria, not based on the random process as in the LEACH protocol. Table 7 lists the average improvement in the KPSO performance compared with both the K-means algorithm and the LEACH protocol. The KPSO algorithm performs more transmissions than the other two algorithms when the number of live nodes is greater than 30% of the total network nodes.

Table 7. Average performance improvement.

Base station location	Average improvement in the no. of transmissions (%)	
	Improvement over K-means	Improvement over LEACH
(0,0)	17.1305%	48.9473 %
(50,50)	5.93225%	1.1655 %
(50,175)	19.0443%	28.6713 %

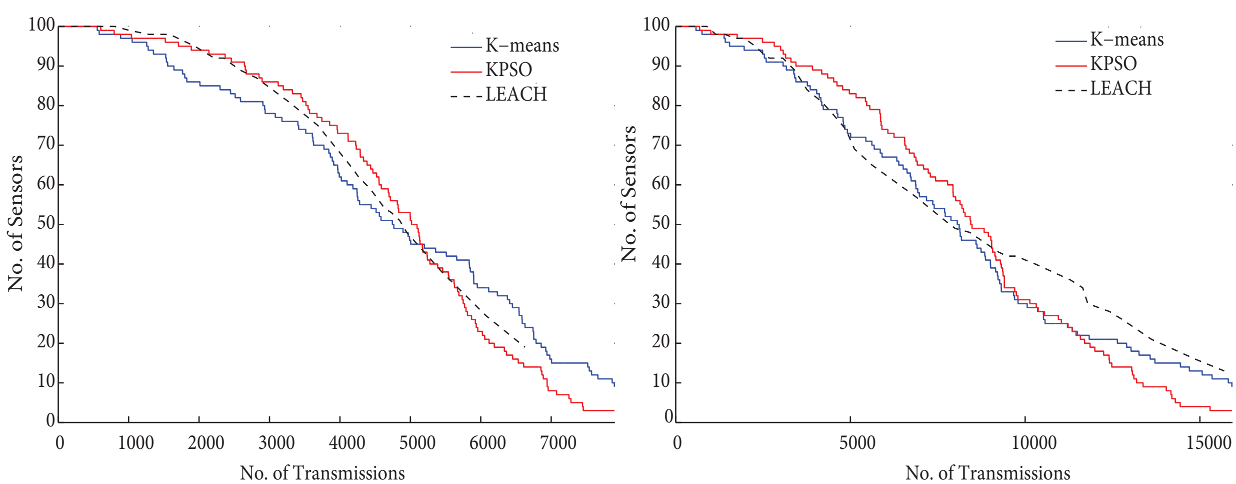

Figure 13. Total number of live sensor nodes with energies of (a) 2 J each, (b) 50% with 2 J and 50% with 5 J.

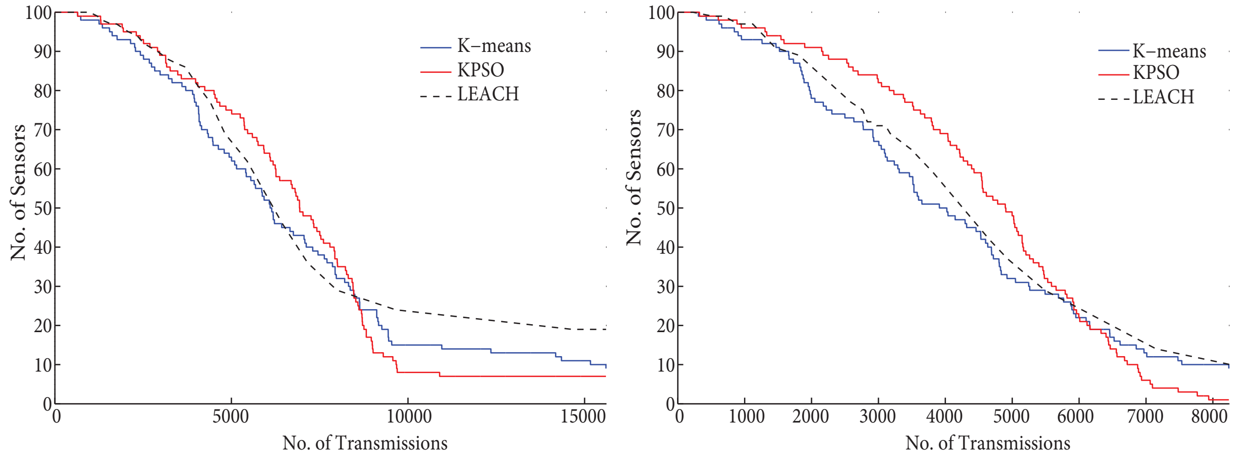

Figure 14. Total number of live sensor nodes when the base station is located at point (a) (50,50) or (b) (50,175) in the environment.

8. Conclusions and future work

A hybrid K-means PSO clustering algorithm was presented and implemented. The algorithm consists of two phases. First, the K-means algorithm is used to partition the WSN into a predefined number of clusters. Second, the PSO algorithm selects the best CH for each cluster. Finally, the evaluation phase runs our developed simulation tool. A novel fitness function that maximizes the network lifetime was provided. The proposed KPSO algorithm showed an average improvement of about 49% over the LEACH protocol and about 18% over the K-means clustering algorithm in the arbitrary studied cases. The proposed algorithm was able to provide a significant improvement of nodes' lifetime in many cases. Finally, we plan to modify our algorithm such that it suits a mobile environment.

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