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FULL-LENGTH ARTICLE

Improved multi-objective weighted clustering algorithm in Wireless Sensor Network

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Abstract In Wireless Sensor Networks (WSNs), the network's performance is usually influenced by energy constraint. Through a well-designed clustering algorithm, WSN's energy consumption can be decreased evidently. In this paper, an Improved Multi-Objective Weighted Clustering Algorithm (IMOWCA) is proposed using additional constraints to select cluster heads in WSN. IMOWCA aims at handling a WSN in some critical circumstances where each sensor satisfies its own mission depending on its location. In addition to fulfill its mission, the sensor tries to improve the quality of communication with its neighboring nodes. Our proposed algorithm divides the network into different clusters and selects the best performing sensors based on residual energy to communicate with the Base Station (BS). IMOWCA uses four critical parameters: $\mathbf{EC}_i$: Energetic Characteristic of sensor i, $\mathbf{DD}_i$: Degree Difference of sensor i, $\mathbf{DC}_i$: Sum of distances between sensor i and its neighbors and $\mathbf{DM}_i$: Mission distance of sensor i. To balance the consumed energy in different formed clusters, a Base Station Genetic Algorithm (BGA) is developed. Simulation results demonstrate that the proposed algorithms are advantageous in terms of convergence to the appropriate locations and efficients in regard to energy conservation in WSNs.

1. Introduction

In recent years, wireless communication and sensor technologies have seen tremendous evolution. Wireless Sensor Networks (WSNs) have emerged as a promising research domain and have been used in a wide variety of applications [1]. They have been used in health field [2,3], Environmental field [4–6], and smart home-field [7]. By means of this recent technology, it becomes possible to interact with the surrounding environment through the use of multiple tiny sensors. WSNs use sensors to co-operatively monitor complex environmental or physical conditions. Such sensors are generally equipped with communication capabilities and data processing in order to collect data and to route information back to a Base Station (BS) [8]. WSNs are examples of resource-constrained networks in which the processing resources, the

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storage and the energy are limited [9]. As a result, this constraint of energy is a critical issue which needs to be tackled so that WSNs can be widely employed. In WSN, the power source consists of a battery with a limited energy budget which results in a finite lifetime of nodes. Moreover, it could be impossible or inconvenient to recharge the battery because nodes may be deployed in a hostile or unpractical environment [10]. In the last few years, several studies have established for the extension of nodes' battery life as much as possible. A survey that offers a comprehensive view of energy-saving solutions in WSNs while taking applications' requirements into consideration is presented in [11].

It is very important to note that in WSN both the network structure and the manner of communication between the nodes decide the energy expenditure. On the plain network, hierarchical structures are generally preferred due to their reliability and improved energy conservation. Clustering is the prominent hierarchical architecture. Cluster formation is one of the early proposed methods for energy efficient operation in WSNs [12].

In clustering, the sensor nodes are divided into different virtual groups according to a set of rules [13]. Some nodes are selected as Cluster Heads (CHs) and the other nodes are called Cluster Members (CMs) [14]. The CHs are responsible for managing the CMs, and being charge of receiving and processing data from them. They are also the nodes having the ability to communicate with the BS directly, while each CM can make a communication just with its own CH (Fig. 1). As a result, CHs consume more energy than their CMs, since they have the responsibility of network organization, data gathering, and long distance data transmissions with the BS [15]. Clustering the nodes in WSNs is performed with different objectives and purposes presented in [16]. The most important and common goal of all these objectives is the energy conservation.

The main contribution of this paper can be summarized as follows: the WSN's clustering in some mission-specific critical situations is not just a single-objective problem, but a multi-objective one; we should consider various aspects of a network concurrently. This optimization is used in several areas related to telecommunication. For example, we site the work presented in [39] where the authors identified a multi-objective dynamic vehicle routing problem (M-DRP) and proposed a Time Seed based solution using Particle Swarm Optimization (TS-PSO) for this problem. We also site the paper [40] aiming at maximizing fault tolerance and minimizing delay in virtual network embedding using Non-Dominated Sorting Genetic Algorithm (NSGA-II). Another approach based on multi-objective optimization is presented in [39], this work deals with a Geocast through Particle Swarm Optimization (GeoPSO) protocol. So, being motivated by the importance of network structure and the manner of communication between the nodes in the energy expenditure under WSN, this work considers jointly those factors (Network structure and communication manner). More precisely, the main objective was to develop a clustering algorithm to solve the energetic constraint in WSNs by the joint minimization of mission and communication costs. In other words, the proposed algorithm aims at ensuring both efficient satisfaction of sensors' mission and improving the quality of communication between them while minimizing jointly the costs of these two operations based on four metrics: $\mathbf{EC}_i$, $\mathbf{DD}_i$, $\mathbf{DC}_i$ and $\mathbf{DM}_i$.

The paper is organized as follows: Section 2 deals with related works. Section 3 is reserved firstly to recall the interest of SGA algorithm in terms of joint minimization of mission and communication costs, secondly to explain and give more details concerning different phases of IMOWCA algorithm, and the final part of this section takes place to show the way to achieve the optimal position of BS using our algorithm BGA, to balance the consumed energy in formed clusters. The numerical result, the possible comparisons, the various analyses and the performances of proposed algorithms are provided in Section 4 which leads to the conclusion and perspectives of our work.

2. Literature review

Many works have been considered for tacking clustering issue and finding good location of nodes in WSNs. For the first challenge, in the last decade, a lot of approaches have been proposed in order to find an energy efficient solution for one of the following clustering problems: Cluster size [17], transmission power load balancing between cluster members [18,19], and CH selection [20,21].

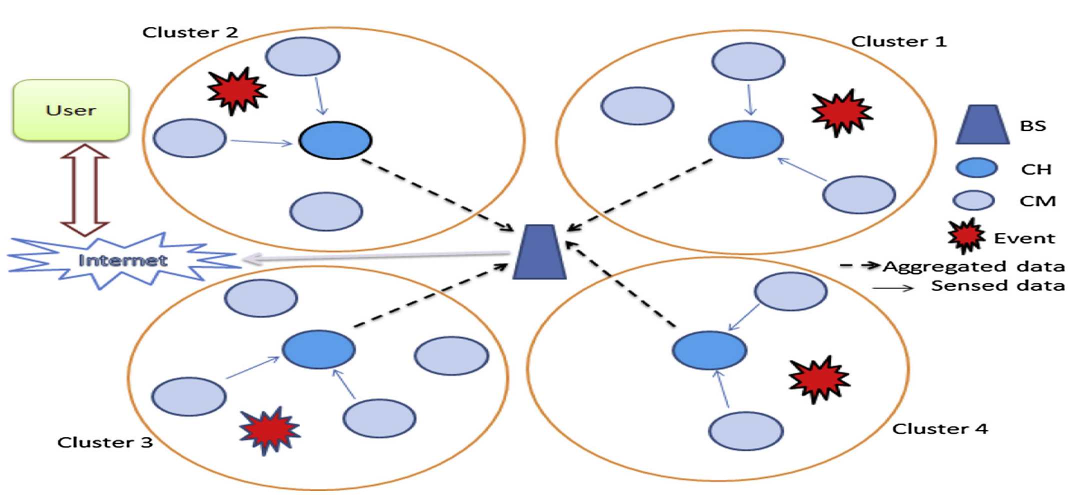

Figure 1 Clustering in WSN.

Moreover, numerous clustering algorithms for WSNs have been proposed in [22] typically aiming at reducing the power consumption. Another algorithm based on a clever strategy of cluster head (CH) selection, residual energy of the CHs and the intra-cluster distance for cluster formation is presented Table 1: Summary of notations in [23].

In 2014, one of the most important surveys on WSN algorithms has been presented in [16] where the authors describe some important clustering approaches in WSNs. Some other hierarchical clustering protocols including LEACH, HEED, TEEN, APTEEN, and EECS are discussed in [24]. In [25] LEACH and its recent advances are studied. A neural network based clustering approaches are presented in [26] which focuses on five neural network based algorithms: ART, ART1, FUZZY ART, IVEBF, and EBCS. In [18], the transmission load assignment in WSNs is modeled as a game. This work focuses on a cluster-based and surveillance-oriented sensor network.

In this context, there is another challenge which is finding a good location for the BS based on initial topological information such as distances between sensor nodes and the BS. However, such schemes are not resource aware and may not lead to the best placement for the BS. In general the sink placement problem is NP-complete [27] and finding the best position of sink is very hard. In recent years, several papers report on BS positioning [28–30,27] and mainly design the network to ensure energy conservation and network lifetime extension. Since the optimal location of BS is one of the important factors in the present approach, recent attempts made in this research area are reminded. In 2015, some new protocols are presented in [31,32]. Others approaches are discussed in [27,33–35].

Table 1 Summuray of notations.

Notations	Meaning
C	Set of sensors
$C_{v(i)}$	Neighbors set of sensor i
S_i	Area in where each sensor i can move freely
(x_i, y_i)	Current position of sensor i
(x_i^s, y_i^s)	Mission's position of sensor i
(x_i^c, y_i^c)	Communication's position of sensor i
(x_i^{op}, y_i^{op})	Optimal location of sensor i
$(x_{bs}^{op}, y_{bs}^{op})$	Optimal location of base station
dij	Distance between sensors i and j
d_{is}	Distance between current and mission's position of a sensor
$f_{ij}^c(dij)$	Cost of communication between sensors i et j
$f_i^s(d_{is})$	Mission cost of sensor i.
α	Path loss exponent
e_0	Energy needed to transmit one unit of data to BS
c	Communication factor
s	Surveillance factor
R	Transmission radius of a sensor
Max	Maximal number of sensors managed by cluster head
CH	Cluster head
CM	Cluster member
S_{CH}	Cluster heads set
S_{CM}	Cluster members set

However, none of these papers considers jointly the cost of mission and the quality of communication, also the network considered is not critical. Our approach is clearly different in terms of these two contradictory objectives: minimizing mission cost and maximizing the communication quality, meanwhile. Thus, we propose a network containing multiple nodes to deploy in two-dimensional space. This network focuses on providing a good communication quality and all nodes are additionally interested in the satisfaction of their missions effectively. The established works in these critical cases are rare. Our previous papers [36–38] are three recent proposals in this context, where we model and solve some problems related to the optimal placement of sensors and BS in WSNs.

3. Materials and methods

3.1. Network model

We suppose that a set of n sensors is deployed in a geographic area of interest to supervise a given physical phenomenon. The topology of a WSNs is represented by the graph $G = (C, E)$, where $C = \{1, 2, \ldots, n\}$ is a set of n sensors and $E \subset C \times C$ is the set of wireless links between the various sensors. $C_{v(i)}$ is the neighbor set of the sensor i. In Table 1, we present the meanings of the notations used in our modeling.

3.2. Optimal placement of sensors using SAG algorithm

Before determining the different clusters constituting the network, we briefly recall the objective of the first phase of our approach which is the reduction in mission and communication costs of each node. For this, we used our SAG algorithm presented in [38]. SAG aims to find the optimal locations of sensors by solving the optimization problem given as follows:

$$minf(x,y) = \sum_i f_i^s(d_{is}) + \sum_i \sum_{j \in C_{v(i)}} cf_{ij}^c(d_{ij}) \tag{1}$$

subject of $(x_i, y_i) \in S_i \quad \forall (i,j) \in C \times C_{v(i)}$

We put the following:

$$f_i^c(d_{ij}) = \sum_{j \in C_{v(i)}} f_{ij}^c(d_{ij}) \tag{2}$$

$$V = (x_1, y_1, x_2, y_2, \ldots, x_n, y_n) \tag{3}$$

$$F_s(x,y) = \sum_i f_i^s(d_{is})(1) \tag{4}$$

$$F_c(x,y) = \sum_i f_i^c(d_{ij}) \tag{5}$$

$$F(V) = f(x,y) \tag{6}$$

So (1) becomes

$$minF(V) = sF_s(V) + cF_c(V) \tag{7}$$

Subject of $V \in \prod_{i=1}^{n} S_i$

The pseudo code of the SAG algorithm is given below.

Algorithm 1. SGA algorithm.

Data: $(x_i^m, y_i^m), (x_i^c, y_i^c), i \in C$
Result: $(x_i^{op}, y_i^{op}), i \in C$
Initialization of population P;
Evaluate P using the function F;
while No convergence
do
  $P' :=$ Selection of parents in P;
  $P' :=$ Apply the crossing operator on P';
  $P' :=$ Apply the mutation operator on P';
  $P :=$ Replace old parents of P by their descendants in P';
  Evaluate P using the function F;
End

Fig. 2 shows the flowchart of SGA.

SGA starts by generating an initial population P (Multiple values of V (Eq. (3)) *de* and evaluating the adaptation of all individuals (Multiple values of (x_i, y_i)) in initial population. Then the individuals are randomly selected for reproduction according to the principle of survival of the fittest. After that the children (or descendants) are generated applying the following two genetic operators: crossover and mutation. Those children are moved to a new population P' and replaced in whole or in part by the children of previous generations. The new population of individuals takes over from one generation to the next until reaching the stopping criterion. We note that after performing several simulations, we have chosen the value $e = 0.0001$ as stop criterion relatively to the evaluation step.

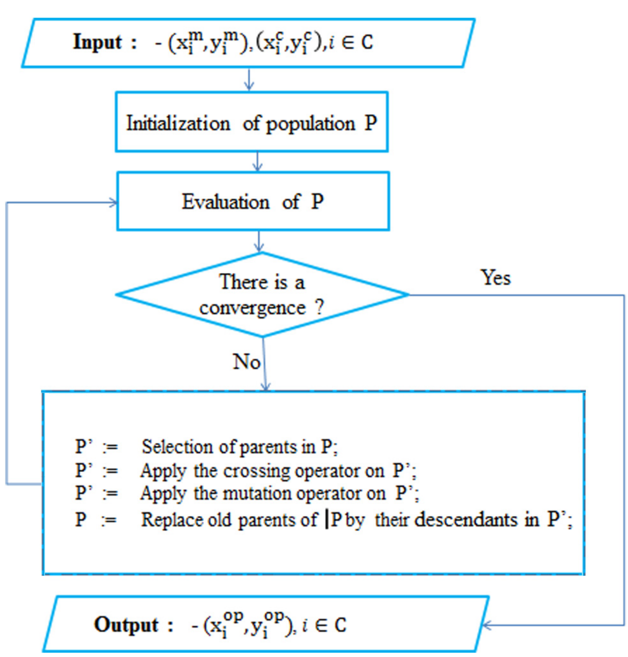

Figure 2 SGA flowchart.

3.3. Description of our algorithm IMOWCA

After calculating the optimal position for each sensor i using SAG, this section presents the main phase of the given approach. Indeed, to solve the energetic constraint and to optimize the resources in mission-critical sensor networks, we developed IMOWCA algorithm based on the following parameters:

- **EC$_i$:** Energetic Characteristic of sensor i.
- **DD$_i$:** Degree Difference of sensor i that is the difference between the degree of sensor i (number of sensors within its transmission radius R) and a predefined ideal node number Max in a cluster.
- **DC$_i$:** Sum of distances between sensor i and its neighbors.
- **DM$_i$:** Mission distance of sensor i.

To determine the different clusters, the IMOWCA algorithm follows these steps:

- **Step 1:** Compute **EC**$_i$ as follows:

$$\mathbf{EC}_i = (T_i \times A)/E_i \tag{1}$$

where T_i is the transmission rate, E_i is the initial energy of sensor i and A is a constant for amplification ($A = 1000$).

- **Step 2:** Determinate the neighbor set $C_{v(i)}$ of each sensor i, where $C_{v(i)}$ is defined by:

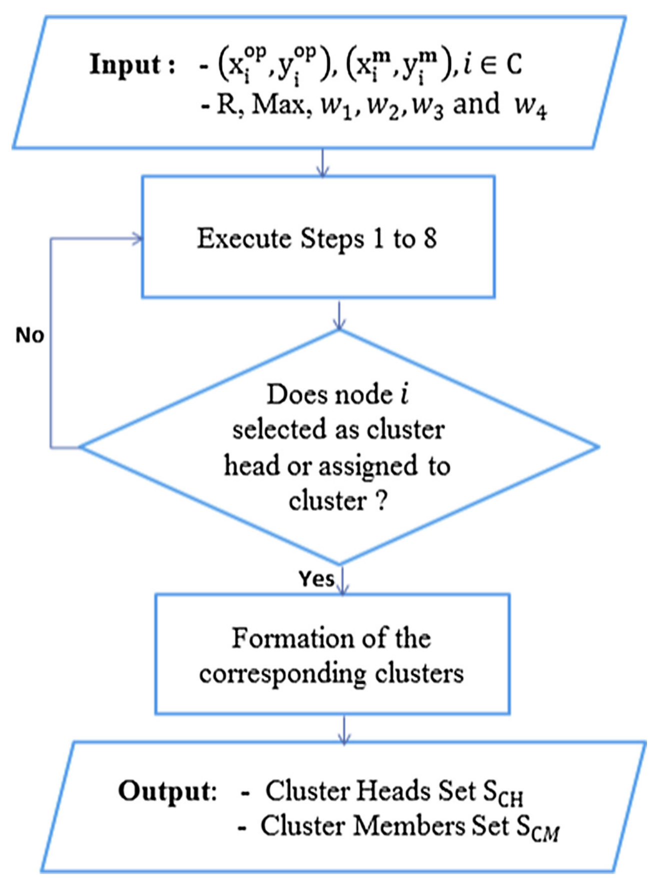

Figure 3 IMOWCA flowchart.

$$C_{v(i)} = \left\{ j \in C \middle/ \left[\left(x_i^{op} - x_j^{op}\right)^2 + \left(y_i^{op} - y_j^{op}\right)^2 \right]^{\frac{1}{2}} \leqslant R \right\} \tag{2}$$

– Calculate the degree d_i of each sensor i defined by: $d_i = \mathrm{Card}(C_{v(i)})$

- **Step 3:** Calculate the degree difference of each sensor i by this formula: $\mathrm{DD}_i = |d_i - \mathrm{Max}|$.
- **Step 4:** Calculate the sum DC_i of the distances between sensor i and its neighbors. That is:

$$DC_i = \sum_{j \in C_{v(i)}} \left[\left(x_i^{op} - x_j^{op}\right)^2 + \left(y_i^{op} - y_j^{op}\right)^2 \right]^{1/2}$$

- **Step 5:** Calculate the parameter DM_i which represents the distance between the optimal position (x_i^{op}, y_i^{op}) of the sensor i and the position of sensor's mission (x_i^s, y_i^s): $\mathrm{DM}_i = \left[\left(x_i^{op} - x_i^m\right)^2 + \left(y_i^{op} - y_i^m\right)^2 \right]^{1/2}$.
- **Step 6:** Calculate the combined weight CW_i as follows:

$$\mathrm{CW}_i = w_1 \times \mathrm{DD}_i + w_2 \times \mathrm{DC}_i + w_3 \times \mathrm{DM}_i + w_4 \times \mathrm{EC}_i$$

where w_1, w_2 and w_3 are different weights such that $w_1 + w_2 + w_3 + w_4 = 1$

- **Step 7:** Select the sensor with the minimum combined weight CW_i as a cluster head.
- **Step 8:** Eliminate the chosen cluster head and its neighbors from the set of original sensor nodes.
- **Step 9:** Execute Steps 1–8 for the remaining sensors until each one is assigned to a cluster.

After the execution of these steps successively, the different clusters are formed and all sensor nodes are regrouped into clusters with correspond CHs.

Fig. 3 shows the flowchart of our algorithm IMOWCA.

3.3.1. Explanatory example

This subsection provides on illustration how the IMOWCA algorithm is running by considering twelve sensors characterized by their initial factors as shown in Table 2.

Also the parameters that are necessary for the operation of the algorithm are defined as follows:

- The threshold number Max is set at 6, which means that a cluster head can conveniently manage 6 sensors.
- The four weights w_1, w_2, w_3 and w_4 are respectively set to the values 0.4, 0.2, 0.2 and 0.2.

Our algorithm proceeds as follows:

Step 1: The Energetic Characteristic of each sensor i is calculated using formula (1).
Step 2: The neighbors set $\boldsymbol{C_{v(i)}}$ of each sensor i and its degree $\boldsymbol{d_i}$ are obtained as shown in Table 3.
Step 3: The degree difference $\mathrm{DD_i}$ of each sensor i is derived using formula (2).
Step 4: The different distances $\boldsymbol{DC_i}$ are calculated by the formula (3). For example,

$$\boldsymbol{DC_1} = \left([(50-75)^2 + (64.3-65)^2]^{\frac{1}{2}} + [(50-65)^2 + (64.3-85.5)^2]^{\frac{1}{2}} + [(50-69.8)^2 + (64.3-115)^2]^{\frac{1}{2}} \right) = 105$$

Step 5: For each sensor i, the distance $\boldsymbol{DM_i}$ is calculated by the formula (4). For example,

$$\boldsymbol{DM_1} = \left([(50-50)^2 + (64.3-60)^2]^{\frac{1}{2}} \right) = 4.3$$

Step 6: For each sensor i, the combined weight $\boldsymbol{CW_i}$ is calculated using formula (5).
After Step 6, the various parameters $\boldsymbol{DD_i}$, $\boldsymbol{DM_i}$, $\boldsymbol{DC_i}$, $\boldsymbol{EC_i}$ and $\boldsymbol{CW_i}$ are calculated and listed in Table 4 (see Fig. 3).

Step 7: The sensor having the smallest value of combined weight $\boldsymbol{CW_i}$ is chosen as a cluster head. Table 4 lists that $\boldsymbol{CW_1}$ is the minimum value of the combined weight. Thus, the **sensor 10** is selected as the first cluster head. Fig. 4 presents the obtained results.
Step 8: The chosen cluster head **(CH: Sensor 1)** and its neighbors (**CMs: Sensors 2, 7 and 5)** are eliminated from the set of original sensor nodes.

Table 2 Sensors initial factors.

Sensor i	(x_i^m, y_i^m)	(x_i^{op}, y_i^{op})	E_i	T_i
1	(50, 60)	(50, 64.3)	7500	5
2	(80, 60)	(75, 65)	7200	6
3	(120, 60)	(122, 66)	6600	6
4	(170, 60)	(165, 65.5)	8400	4
5	(70, 80)	(65, 85.5)	10,000	5
6	(140, 90)	(136, 90.5)	7600	4
7	(70, 110)	(69.8, 115)	9600	4
8	(110, 120)	(107, 126)	9000	5
9	(150, 110)	(145, 114)	8500	5
10	(140, 130)	(133, 137)	9600	6
11	(110, 150)	(105, 155)	9600	4
12	(60, 150)	(57.4, 156)	8000	5

Table 3 $C_{v(i)}$ and d_i values for each sensor i.

Sensor i	$C_{v(i)}$	d_i
1	{2, 5, 7}	3
2	{1, 3, 5, 7}	4
3	{2, 4, 6, 9}	4
4	{3, 6, 9}	3
5	{1, 2, 7, 8}	4
6	{3, 4, 8, 9, 10}	5
7	{1, 2, 5, 8, 11, 12}	6
8	{5, 6, 7, 9, 10, 11, 12}	7
9	{3, 4, 6, 8, 10, 11}	6
10	{6, 8, 9, 11}	4
11	{7, 8, 9, 10, 12}	5
12	{7, 8, 11}	3

Table 4 DC_i, $DM_i DD_i$ and CW_i values for each sensor i.

Sensor i	DC_i	DM_i	DD_i	EC_i	CW_i
1	105	4,3	3	0,133333	23,19333333
2	155	7,0711	2	0,166667	50,25466333
3	171	6,3246	2	0,181818	54,90647091
4	133	7,433	3	0,095238	43,80609048
5	163	7,2863	2	0,1	52,38589
6	184	4,0311	1	0,105263	57,33564579
7	269	5,004	0	0,083333	82,61786667
8	298	6,7082	1	0,111111	92,36801556
9	253	6,4031	0	0,117647	78,40916529
10	100	9,8995	2	0,125	34,39485
11	220	7,0711	1	0,083333	68,93799667
12	148	6,5391	3	0,125	48,18673

Fig. 5 shows the obtained results after removing the first cluster head and its neighbors.

The steps from 1 to 8 are repeated for the remaining sensors until each sensor is assigned to a cluster. The final results of clustering are shown in Fig. 6.

3.4. Balancing consumed energy in formed clusters by placing BS in the best location

The main goal here is to determine the best position BS relatively to different clusters formed. For this, we consider that the base station has relatively sufficient energy. We determine the optimization problem that minimizes the total energy consumed by active sensors in the network as follows:

$$ming(x,y) = e_0 \sum_{i\in A} \left[(x_i^{op} - x)^2 + (y_i^{op} - y)^2 \right]^{\alpha/2} \quad (8)$$

where $A = S_{CH}$.

Theoretically, the solution is one of the critical points of g; in other words, the total energy used is minimal when:

$$\frac{\partial g}{\partial x} = 0 \text{ and } \frac{\partial g}{\partial y} = 0 \quad (9)$$

We have:

$$\frac{\partial g}{\partial x} = \frac{\partial}{\partial x}\left[e_0 \sum_{i\in A} \left(\sqrt{(x_i^{op} - x)^2 + (y_i^{op} - y)^2} \right)^{\alpha} \right]$$

$$= e_0 \alpha \sum_{i\in A} \left(\sqrt{\left((x_i^{op} - x)^2 + (y_i^{op} - y)^2\right)} \right)^{\alpha-1} \times \frac{\partial}{\partial x}$$

$$\times \sqrt{\left((x_i^{op} - x)^2 + (y_i^{op} - y)^2\right)}$$

$$= e_0 \alpha \sum_{i\in A} (x - x_i^{op}) \left[(x_i^{op} - x)^2 + (y_i^{op} - y)^2 \right]^{\frac{(\alpha-2)}{2}} \quad (10)$$

and similarly:

$$\frac{\partial g}{\partial y} = e_0 \alpha \sum_{i\in A} (y - y_i^{op}) \left[(x_i^{op} - x)^2 + (y_i^{op} - y)^2 \right]^{\frac{(\alpha-2)}{2}} \quad (11)$$

Unfortunately there is no closed formula solution to find the optimal coordinates $(x_{bs}^{op}, y_{bs}^{op})$, and thus we implement the following algorithm to find the best location of the base station [38]. The pseudo code of the BGA algorithm is presented below.

Algorithm 2. BGA algorithm.

Data: (x_i^{op}, y_i^{op}), $i \in S_{CH}$, e_0, α
Result: $(x_{bs}^{op}, y_{bs}^{op})$
Initialization of population P;
Evaluate P using the function F;
while No convergence
do
  $P' :=$ Selection of parents in P;
  $P' :=$ Apply the crossing operator on P';
  $P' :=$ Apply the mutation operator on P';
  $P :=$ Replace old parents of P by their descendants in P';
  Evaluate P using the function F;
End

In order to determine the optimal solution $(x_{bs}^{op}, y_{bs}^{op})$, the BGA algorithm follows the same steps as SGA (Section 3.2).

4. Results and discussion

This section displays numerical results given by the three algorithms SGA, BGA and IMOWAC. The cost functions and parameters are defined as follows [38]:

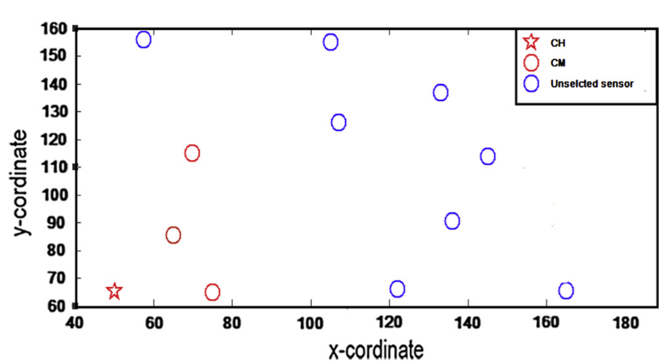

Figure 4 Selection of the first cluster head.

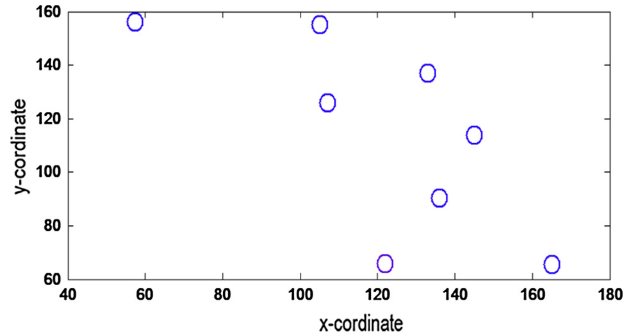

Figure 5 The remaining sensor nodes after the first iteration.

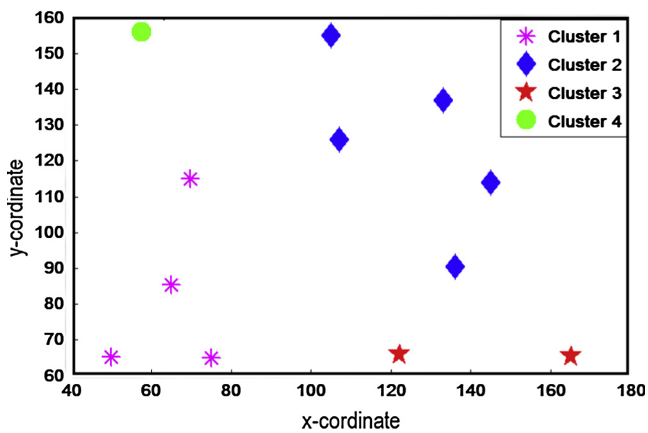

Figure 6 The final results of clustering using IMOWCA.

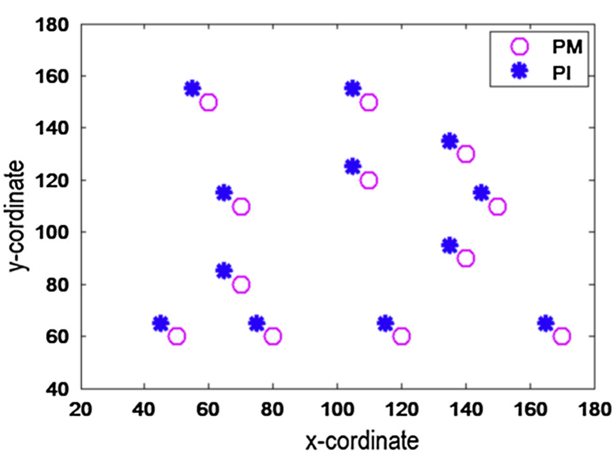

Figure 7 The mission and communication's position of each sensor *i*.

- $f^c_{ij}(d_{ij}) = 100\exp(10/12(\log_2(10^6(d_{ij}))));$
- $f^s_{ij}(d_{is}) = 5\exp(10^{-2}d_{is} - 1);$
- $C = \{1, 2, \ldots, 12\}$ and $e_0 = 15 \cdot 10^{-3}$ mJ;
- $w_1 = 0.4$, $w_2 = 0.3$, $w_3 = 0.3$ and Max $= 6$;
- For $i \in C$, the values of (x^m_i, y^m_i) and (x^{op}_i, y^{op}_i) are shown in Table 2.

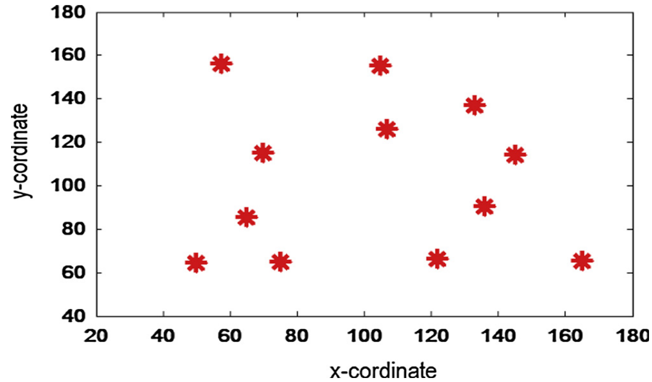

Figure 8 The best locations of sensors given by SGA.

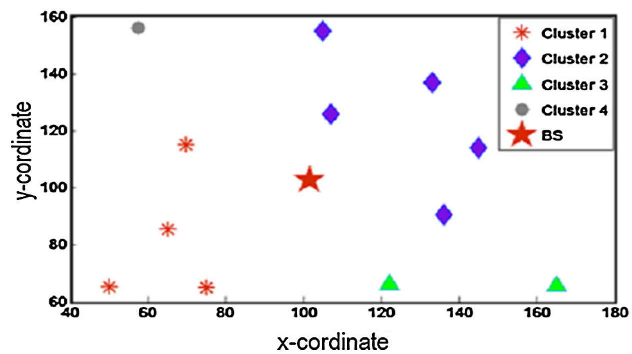

Figure 9 Different clusters given by IMOWCA.

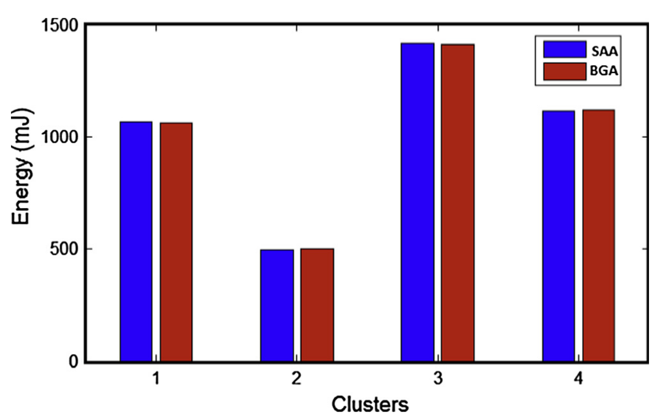

Figure 10 Consumed energy in different clusters.

The considered network is shown in Fig. 7, which constituted of 12 nodes, where PM and PI denote respectively the mission and communication's position of each sensor *i*.

The best locations of sensors calculated using SGA are represented in Fig. 8.

After balancing mission and communication's costs for each sensor, the IMOWCA algorithm is executed to form the different clusters and determine explicitly the two sets S_{CH} and S_{CM}. Later on, the base station is placed in its best

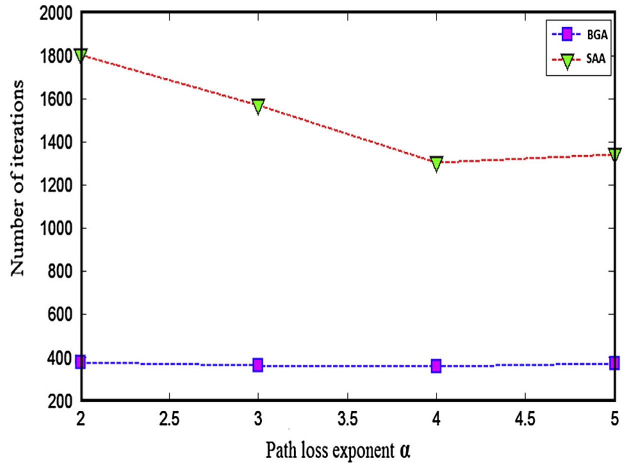

Figure 11 The convergence of SAA and BGA.

position relatively to the different clusters formed. The results of this clustering are shown in Fig. 9.

Note that the best position of BS is calculated using two methods: Simulating Annealing Algorithm SAA [42] and BGA. The total energy consumed by active sensors in the network is calculated. Fig. 10 illustrates this energy in both cases.

The comparison between SAA and BGA shows that the amount of consumed energy is the same in both cases. While the BGA algorithm is very advantageous in terms of convergence, this fact is shown clearly in Fig. 11.

The performance of the BGA algorithm against SAA is justified by the advanced techniques of genetic algorithms that have passed from the stage of basic research to applied research. Indeed, in terms of convergence, SAA is negatively influenced by the choice of the initial solution which is one of the most important criteria for SAA. So, to achieve the final solution, SAA searches only in the vicinity of the initial solution. By cons, after coding the chromosomes, the BGA algorithm (Algorithm 2) can start with any initial population, and then performs a global search to reach the best solution. Thus, BGA evolves this population by selecting the best individuals. Then, thanks to the operation of croissant, it evolves also these individuals with possible mutations.

Later on, another distinguishing point of BGA algorithm is noted. Indeed, for optimizing the objective function, BGA does not impose any regularity (Continuity, differentiability, convexity, etc.) about this function.

By comparing the IMOWCA algorithm with SAG, it seems obvious, from Fig. 12, that MOWAC is more efficient. Specifically, it is clear that the total consumed energy (by millijoule [mJ]) in the network has decreased remarkably. This means that MOWAC saves a lot of energy which is to date a great challenge for researchers in the area of WSN.

On the one hand, the IMOWCA performance is justified by the fact of introducing the different metrics DD_i, DC_i and DM_i (for each sensor i) in the function to be optimized. Indeed, the IMOWCA algorithm benefited greatly from the importance of multi-objective optimization used. This technique allows IMOWCA to consider the different critical parameters in the network studied namely, the mission cost, the communication cost and also the distance between sensors and BS. On the other hand, thanks to the clustering performed by IMOWCA, only the best performing sensors in terms of power are selected to communicate with BS, which is advantageous as regards energy consumption in WSN.

5. Conclusion

In this work we have proposed an improved multi-objective weighted clustering algorithm in order to resolve the energy problem in critical WSNs where each node tries to minimize the weighted sum of mission and communication cost in a distributed way. The proposal approach is based on advanced techniques of genetic algorithms. The obtained results show that, comparing to other techniques, the presented algorithms in this work are advantageous in terms of convergence to the optimal solution. Thus, thanks to the BGA algorithm the number of iterations has decreased clearly from 1600 to 400 (Fig. 11). The different simulations display that total consumed energy in the network has decreased remarkably with around 45% (Fig. 12). This means that the presented algorithms minimize more and more the energy which is the great challenge of WSN's researches.

Therefore, our future work will have to deal with both objectives. The first one is the proposition of new protocols

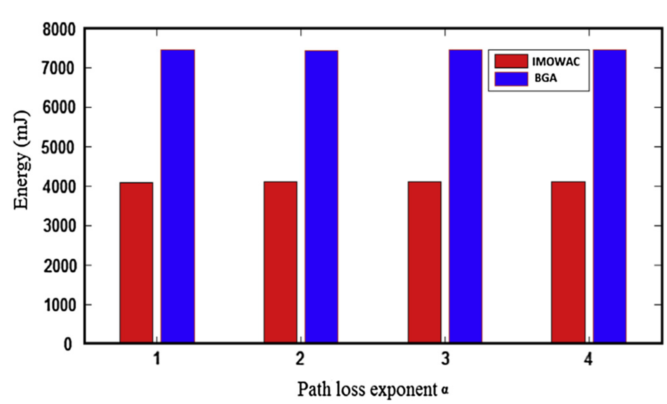

Figure 12 IMOWCA compared with SGA.

concerning node mobility. The second one takes part in routing protocols incorporating the concept of clustering.

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