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Determining Cluster-Heads in Mobile Ad-Hoc Networks Using Multi-Objective Evolutionary based Algorithm

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Abstract

A mobile ad-hoc network (MANET), a set of wirelessly connected sensor nodes, is a dynamic system that executes hop-by-hop routing independently with no external help of any infrastructure. Proper selection of cluster heads can increase the life time of the Ad-hoc network by decreasing the energy consumption. Although different methods have been successfully proposed by researchers to tackle this problem, nearly all of them have the deficiency of providing a single combination of head clusters as the solution. On the contrary, in our proposed method, using a Multi-Objective Genetic Algorithm, a set of near optimum solutions is provided. In the proposed method, energy consumption, number of cluster heads, coverage and degree difference are considered as objectives. Numerical results reveal that the proposed algorithm can find better solutions when compared to conventional methods in this area namely, weighted clustering algorithm (WCA), comprehensive learning particle swarm optimization (CLPSO) and multi objective particle swarm optimization(MOPSO).

Keywords: *Mobile Ad-Hoc Network, Multi Objective Genetic Algorithm, Cluster-Head*

1. Introduction

A mobile ad-hoc network (MANET), which is composed of wirelessly connected sensor nodes, is a self-organizing and infrastructure-less network that can be employed effectively in an environment where no infrastructure is available [1-4]. Since MANETs are also self-organizing and multi-hop communication networks, they have been widely used in crucial areas of disaster recovery, military tasks and battlefield monitoring [5-7].

The unique characteristics of MANETs and their independence from a centralized station have made their design problematic and challenging. The life time of MANETs is an important issue that can be increased by employing clustering method and organizing the sensors in meaningful groups based on their similarities.

Clustering divides all individuals in a way that each member of the network belongs to a single group. For each group, a special node, which is called a cluster-head (CH), carries out the task of resource allocation to all nodes of its corresponding cluster. The topology of the network and the formation of clusters is the responsibility of the CHs. The sensors within the transmission range of any CH belong to its neighborhood. Minimizing the number of CHs, which is an NP-hard problem, is an essential issue since the cluster-heads configuration is changing frequently by the dynamic-in-nature mobile nodes [8]. When a network is divided by clustering, only few nodes become involved for doing the main tasks such as routing, management and data aggregation and therefore the energy efficiency is improved and consequently its lifetime is increased.

Optimization is a process in which the best solution of a problem is found from a set of all the possible solutions. Recently, optimization is wildly used in many applications [9-19]. Most of the real world problems contain two or more conflicting objectives that should be considered at the same time. Before the emergence of the evolutionary computation, the so-called multi-objective optimization problems (MOPs) have challenged the traditional mathematical techniques for a long time. Most of these techniques are not efficient in solving MOPs as they only generate a single solution while the evolutionary algorithms efficiently solve the MOPs and provide a set of near-optimal solutions [20].

In this paper, the problem of finding the minimum number of cluster –heads in an Ad-hoc sensor network is dealt by a novel method based on non-dominated sorting genetic algorithm II (NSGA-II). The proposed method is superior to the existing methods since various objectives, such as cluster head degree, number of cluster heads, coverage and degree difference are considered at the same time. Moreover, the proposed method provides a set of optimal or near-optimal solutions called optimal Pareto front.

The remainder of the paper is organized as follows. The related works are presented in Section 2. The concept of multi-objective optimization is introduced in Section 3. The proposed method and numerical results are presented in Section 4 and Section 5 respectively. Finally the conclusions are drawn in Section 6.

2. Related Works

Bakar and Emphermides [21] proposed a clustering approach where at each neighborhood the host with the highest identification number was selected as the cluster-head. The so called synchronous distributed cluster formation approach has the deficiency of requiring the number of hosts to be known a priori. Lin and Gerla [22], on the contrary, presented an approach where the lowest ID node at each neighborhood was selected as the cluster-head. The neighbors of the selected node are considered as its cluster members. The selecting process is continued until each member is either selected as a cluster head or a cluster member.

Gerla and Tsai [23] proposed a priority-based clustering algorithm called HD algorithm where the node with the highest priority is selected as the cluster-head. The degree of a host is described as the number of its one-hop neighbors. The main issue with the HD algorithm is that the host mobility frequently changes the cluster-heads. In this study, the numerical results of the proposed method are compared with those obtained by HD algorithm as a baseline.

Chatterjee et al. [24] proposed the first weighted clustering algorithm (WCA) for MANETs where the weight of each element is calculated considering various parameters such as battery power mobility and transmission range. The luster heads are then selected based on their weights. The setback of WCA is that firstly, its computational time is dependent on the size of the network and therefore would not be efficient for large ones and secondly, it is a single-objective algorithm and generates a single solution. The main advantage of WCA is its relatively low computational and communication cost.

DAS et al. [25] employed a genetic algorithm-based approach for finding the optimum number of cluster-heads in an ad-hoc network. Similar to WCA, a specific weight is assigned to each objective of the problem which makes the proposed meta-heuristics a weighted-based single-objective algorithm that generates a single solution in each run.

In [26], a new method based on D-hops and mobility pattern of the nodes in MAETs, a variable-diameter cluster formatting is proposed. The distance variation of nodes and consequently their relative motilities are determined by a new metric. The relative mobility of cluster members, which determines the stability of clusters, is also estimated. The main improvement of this algorithm is that the diameter of the clusters, unlike the previous approaches, is not limited to two hops and could vary flexibly considering the stability of the clusters. In this approach, a cluster contains a set of nodes that have relatively comparable moving patterns.

Shahzad et al. [27] proposed a comprehensive learning particle swarm optimization (CLPSO) algorithm for clustering in MANETs. The proposed approach is basically a weighted algorithm where a weight is assigned to each of the network parameters that are transmission power, ideal degree, mobility of the nodes and battery power consumption of the mobile nodes. Each particle consists of information on the cluster-heads and their corresponding members.

The common deficiency of all the proposed evolutionary-based clustering approaches is that they do not consider all the required parameters of MANETs when the clustering is performed. Moreover, WCA, as the first attempt to include all the network parameters, does not deal with the optimal number of cluster-heads and it should be known a priori. It converts the multi-objective problem to a single one by assigning weights to each objective and therefore generates a single final solution. On the contrary, the proposed non-dominated sorting genetic algorithm II based clustering algorithm deals with all the network parameters at the same time while produces a set of optimal or near-optimal final solutions.

3. Multi Objective Algorithms

3.1 Multi objective problem

Multi-objective problems (MOP) include several conflicting objectives that should be either minimized or maximized at the same time. Many real world problems have to be considered as MOPs since there is more than a single objective to be considered when the problem is being solved. Since in an Ad-Hoc sensor network various objectives such as cluster head energy, number of cluster heads, cluster head coverage and degree are considered at the same time, the problem is a MOP. An MOP can be mathematically described as follows.

Minimize

$$\vec{f}\left(\vec{x}\right)=\left[f_1\left(\vec{x}\right)\cdot f_2\left(\vec{x}\right)\cdot\ldots\cdot f_k\left(\vec{x}\right)\right] \quad (1)$$

Subject to:

$$g_i\left(\vec{x}\right)\leq 0 \qquad i=1.2.\ \ldots\ .n \quad (2)$$

$$h_i\left(\vec{x}\right)=0 \qquad i=1.2.\ \ldots\ .p \quad (3)$$

Where $\vec{x} = [x_1 . x_2 . \dots . x_n]^T$ is the vector of decision variables, $f_i : R^n \rightarrow R. i = 1.2. \dots . k$ are the objective functions and $g_i . h_j : R^n \rightarrow R. i = 1.2. \dots . \mathrm{m}.\ j = 1.2. \dots . p$ are the given inequality and equality constraints, respectively.

A solution vector is called a Pareto optimal solution if no solution vector can be found that has better performance than it in at least one objective without simultaneously diminishing the effect of any other objective. This concept, instead of producing a single solution, almost always gives a set of solutions that are called the Pareto optimal set or Pareto optimal solutions. The corresponding objective vector of a Pareto optimal solution is referred to as the non-dominated vector. The plot of the objective functions using the set of all non-dominated solutions is called the Pareto front [5, 28].

In MOPs, a solution is only valuable if it is close to the true Pareto-front. For a set of non-conflicting objectives, the Pareto optimal set would have only one member. Therefore, a Pareto optimal front exists if and only if the objectives conflict.

A solution, S_1, dominates solution S_2 if and only if the following two conditions are satisfied [5].

1- Considering all objectives, the solution S_1 is better than or similar to S_2.

2- The solution S_1 is strictly superior to the S_2, at least in one objective.

If S_1 dominates S_2, based on the above-mentioned conditions, then it is considered as a better solution. Two solutions are called non-dominated if neither dominates the other when they are compared in the context of all objective functions.

For any given set of solutions, a comparison of all possible pairs identifies all the dominated and non-dominated solutions. Finally, a set of non-dominated solutions is presented as the Pareto front solutions. The curve that joins these solutions is called the Pareto optimal front [28, 29]. All solutions on this curve are defined as Pareto front solutions. For a problem with two conflicting objectives, the Pareto-front solutions are presented in Figure. 1.

3.2 Fast and Elitist Multi-Objective Genetic Algorithm

Multi-objective genetic algorithm (MOGA) has been widely employed in various problems [30-32]. To improve its performance, Pareto ranking and fitness sharing approaches were implemented into MOGA and non-dominated sorting genetic

algorithm (NSGA) was proposed [30]. Apart from its success, high computational time, premature convergence and the necessity of assigning the sharing parameters were the main deficiencies of this algorithm.

As a response to the new findings where the applicability and usefulness of elitism in enhancing the performance of GA and preventing the loss of good solutions was indicated [33,34], elitism non-dominated sorting genetic (NSGA-II) was proposed [16].

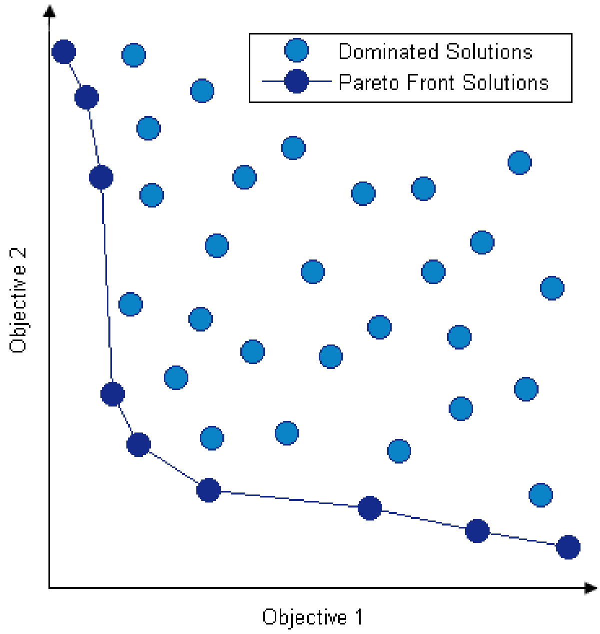


Figure. 1. Pareto-front solutions

This new version, which successfully overcomes the existing problems of NSGA, is employed in this study.

NSGA-II is basically a GA, with even identical initialization and reproduction processes, that employs multi-objective searching technique that are fast non-dominated sorting, shown in Table 1, crowded comparison and a controlled elitism mechanism.

Moreover, a circulation crossover is employed for maintaining the superb genes of the parent population [35].

Considering K individuals in a population$(x_1, x_2,..., x_k)$ first set of parents would be(x_1, x_2) , the second one is $(x_2. x_3)$ and so on. Similarly, the last child is produced considering $(x_k. x_1)$ as parents.

The above mentioned pseudo-code contains two separate parts. In Part A the non-dominated solutions are selected from the set of all solutions. For any vector, *p*, from the set of all vectors, P, the number of solutions that dominate this vector is noted as Np and Lp is the set of solutions that are dominated by this vector. In part B, the remaining dominated solutions are ranked. Rank 2 is the solutions that are only dominated by the set of non-dominated solutions (Rank 1) and dominate all the remaining solution vectors. Similarly, Rank 3 is the solutions that are only dominated by the set of vectors in Rank 1 and Rank 2. The number of ranks has no limits and depends on the nature of the problem being solved.

Table 1. fast non-dominate sorting

Input: *Population P*
Output: *Non-dominated fronts*

```
PART A:
  F_1 = ∅
  FOR each p ∈ P DO
     N_p = 0 , L_p = ∅
     FOR each q ∈ P DO
        IF (p ≺ q) THEN
           L_p = L_p ∪ {q}
        END IF
        IF (q ≺ p) THEN
           N_p = N_p + 1
        END IF
     END FOR

     IF (N_p = 0) THEN
        F_1 = F_1 ∪ {p}
     END IF
  END FOR

PART B:
  c = 1
  WHILE F_c ≠ ∅ DO
     K = ∅
     FOR each p ∈ F_c DO
        FOR each q ∈ L_p DO
           N_q = N_q − 1
           IF (N_q = 0) THEN
              K = K ∪ {q}
           END IF
        END FOR
     END FOR
     c = c + 1
     F_c = K
  END WHILE
```

4. Proposed Method

In the proposed method, a distinctive, random and not-repeatable number within the range of 1 to N (the number of sensors) is assigned to each sensor. The length of each chromosome of the initial population is equal to N (the number of environmental sensors). In other words, each gene in the chromosome represents a sensor which is assigned 1 and 0 for cluster-head sensors and ordinary sensors respectively. The steps of the proposed method are as follows.

Step 1: The initial population is formed within the first step of the proposed method. First chromosome of the initial population is formed by randomly selecting one of the sensors as the cluster head. The corresponding cell in the chromosome is assigned 1. Then, all sensors which are located within the transmission range of this sensor will select the sensor as the cluster head and number 0 is placed in their corresponding cells. After removing all the selected sensors from the list, this process is repeated until all sensors would be selected either as the cluster head or as non-cluster. All chromosomes of the initial population are created with the same process. This step is demonstrated in Figure 2.

Step 2: To evaluate the four diverse objectives of each chromosome, the value of each objective is determined for every cluster-head independently, and then the attained values of each objective for all cluster-heads are added to calculate the objective value of the chromosome. Table2 shows an example for calculating objectives for one chromosome. The calculation of these four objectives is as follows.

1- Energy Consumption: The amount of energy consumed by every cluster head is calculated through equations presented in section 5-2-4.

2- Number of Cluster Heads: The number of available cluster heads of a chromosome is calculated.

3- Degree Difference: This value for each cluster head is calculated as $\Delta = |D - \delta|$ where D is the total number of neighbors of cluster head, δ is the pre-defined threshold level, and Δ indicates the Degree Difference.

4- Coverage Sensor: This is the number of sensors which are located within the range of cluster head sensor.

Step 3: The total population are ranked and sorted according to NSGA-II algorithm.

Step 4: Two-point cross over with probability of 0.9 and mutation rate of 0.01 are applied to generate offspring. These parameters are selected regarding to T.Back's statement that the optimal value of mutation rate is about the inverse of the chromosome length [36].

Step 5: For offspring generated from cross over operator or mutation, there is a possibility that some of the sensors would not be a member of one of the cluster heads. Therefore, a local search should be applied to ensure that all sensors are within a range of one of the cluster heads. To do so, after identifying the non-member sensors, one of them is randomly selected as a cluster head and others which are located within its transmission range are chosen as its members. This procedure is continued until all non-member sensors are selected either as a cluster head or a member.

Step 6: The second, third, and forth steps will be repeated until reaching termination criteria.

The details of the proposed NSGA-II based clustering approach is presented in table 3.

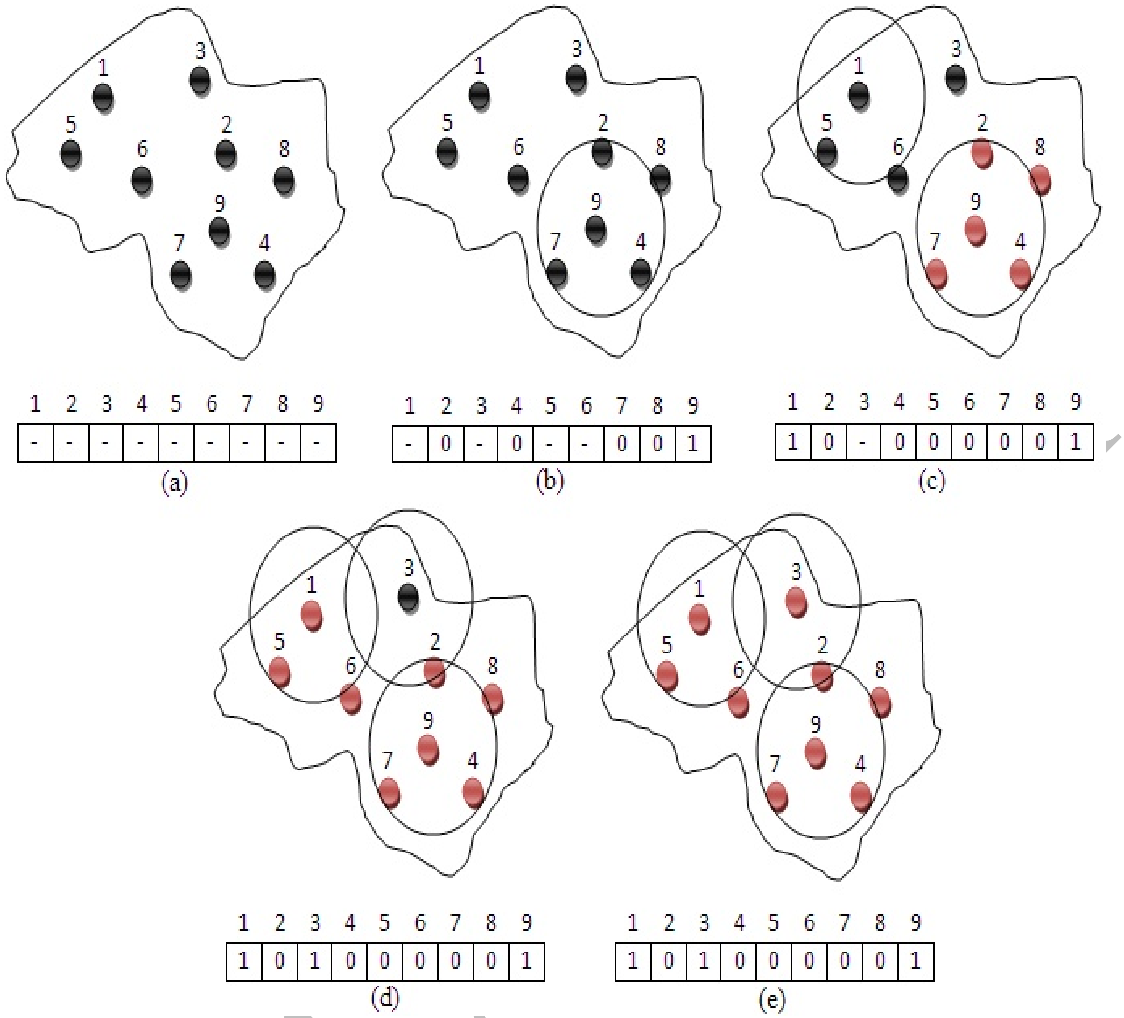


Figure 2. Process of create a population

Table2. Example for calculating objectives for one chromosome

	Cluster-Heads				
	S5	**S8**	**S9**	**S14**	**Sum of Objective Value**
Energy Consumption	0.0065	0.0097	0.013	0.0039	0.0331
Number of Cluster-Heads	1	1	1	1	4
Degree Difference	2	3	6	4	15
Coverage Sensor	6	7	10	8	31

Table3. Proposed NSGA-II algorithm

Input: Wireless *Sensors*
Output: Best *Cluster-Heads*

```
Randomly distribute the position of all the sensors
Initialize the general parameters of NSGA-II
For each chromosome X
DO
   WHILE the entire network is not covered
    DO
      Select a cluster head Xi arbitrarily
       Find the neighbors of the cluster-head
       Without considering the 'ith' cluster-head and its neighbors, find the next cluster-head
    END WHILE
END FOR
WHILE maximum number of cycles not reached
DO
   Evaluate each chromosome with four different objectives
   Sort all chromosomes according to their objectives by NSGA-II
   Ninety percent of the best chromosomes goes for create offspring
   Do circulation selection, two point crossover and mutation
   Do local search on offspring
   Increment the loop counter
END WHILE
```

5. Results and Discussion

5.1 Initial setup

The proposed method is implemented by MATLAB 7.8 Software on a 1.75 GHz and 512 MB PC. General specifications of the environment and the initial set-up are as follows:

- Dimensions of the implementation environment:100×100, 200×200, and 300×300
- The number of environmental sensors: 30 to 60
- The variation of transmission range: 10 to 60
- The number of initial population: 100
- The number of iterations: 150

MOPSO, CLPSO and the proposed method parameters are set as follows:

a) The inertia weight w is set to 0.694
b) The learning factors c1 and c2 are set to 2.
c) Mutation and crossover rate are set to 0.9 and 0.01 respectively.

5.2 Computational results

Overall, this section is classified in according to the performing of two types of tests: The determination of the number of cluster heads and the measurement of energy consumption. Within each of these tests, the proposed method is compared with WCA [24], CLPSO [27], and MOPSO [5].

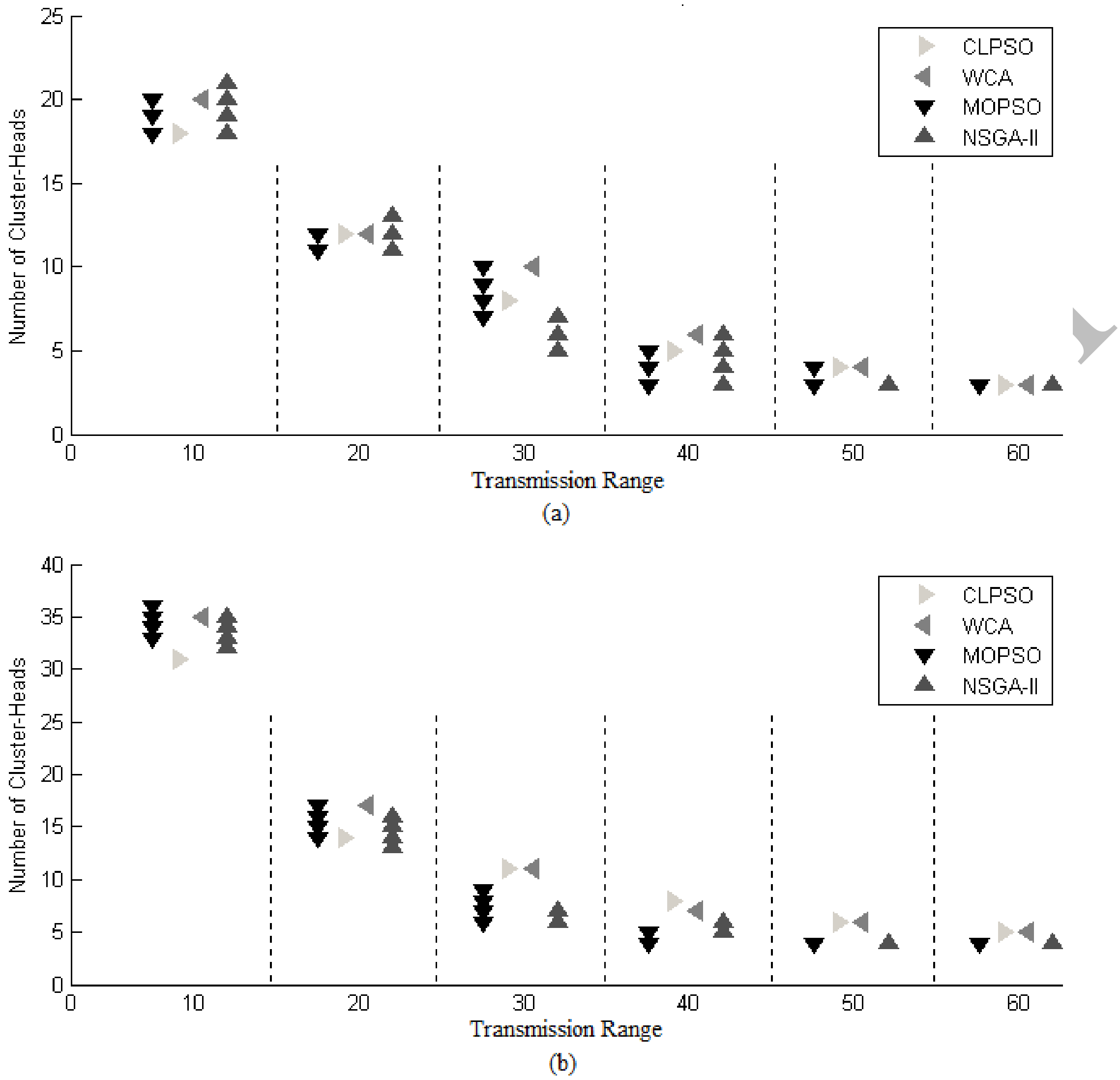


Figure3. The effect of transmission range on the number of clusters by CLPSO, WCA, MOPSO, and NSGA-II methods in a 100 m × 100 m area and the number of nodes is fixed to 30 and 60 in (a) and (b) respectively

5.2.1 The effect of transmission range

During the first test, the number of cluster heads is achieved for the variation of transmission range of sensors by different methods within the range of 10 to 60. The test results for 30 and 60 sensors within the environmental dimensions of 100×100 are shown in Figure 3.

As it could be seen in Figure 3, the same value within each transmission range is determined as cluster head by CLPSO and WCA methods, while there are several optimum values by NSGA-II and MOPSO methods at each step because of the nature of these algorithms. Therefore, the proposed method either determine lower number of cluster heads or its result is equal to the results obtained by other methods at different transmission range. Then we will repeat the previous test for 40 and 50 sensors within an environmental dimension of 300×300. The results are shown in Figure 4.

5.2.2 The effect of network nodes

In another test, the number of sensors is varied within the range of 20 to 60. Then the number of clusters determined by different methods is obtained for sensors with constant range of 20 and 40. The dimensions of the environment are 100 × 100. The results are shown in Figure 5.

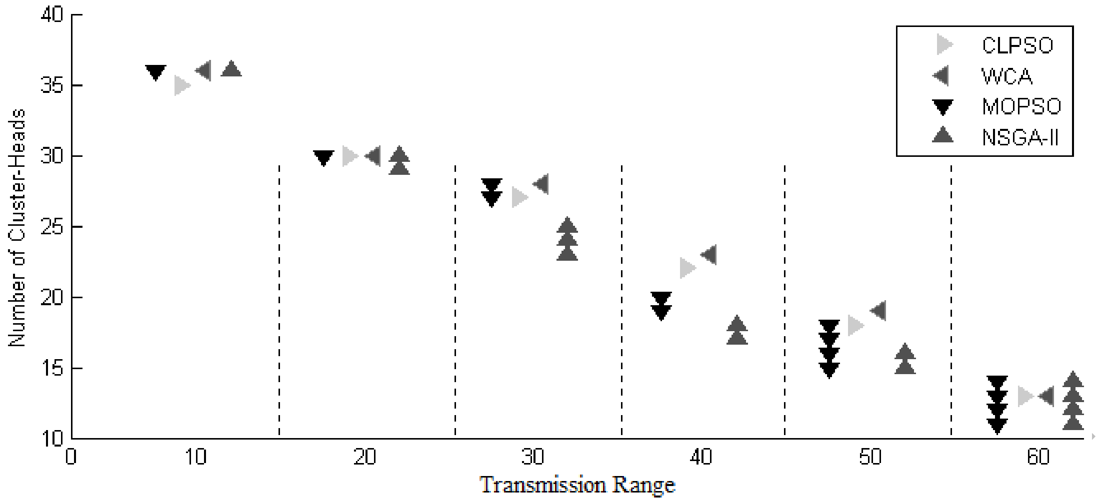
In a similar test, the transmission range of sensors is fixed at 10 and 30 and the obtained cluster heads are calculated by different methods within a 200 × 200 environment (Figure 6).

It can be concluded from Figures 3 and 4 that generally the number of cluster heads is less than that of presented by WCA, CLPSO and MOPSO. Moreover, similar to MOPSO, different solutions are presented at the final stage of the algorithm that in turn gives the flexibility to the design of the network through presenting different sets of network's cluster heads configuration. However, it is worth mentioning that when the transmission range is small (10 and 20), the presented results of different algorithms are very competitive.

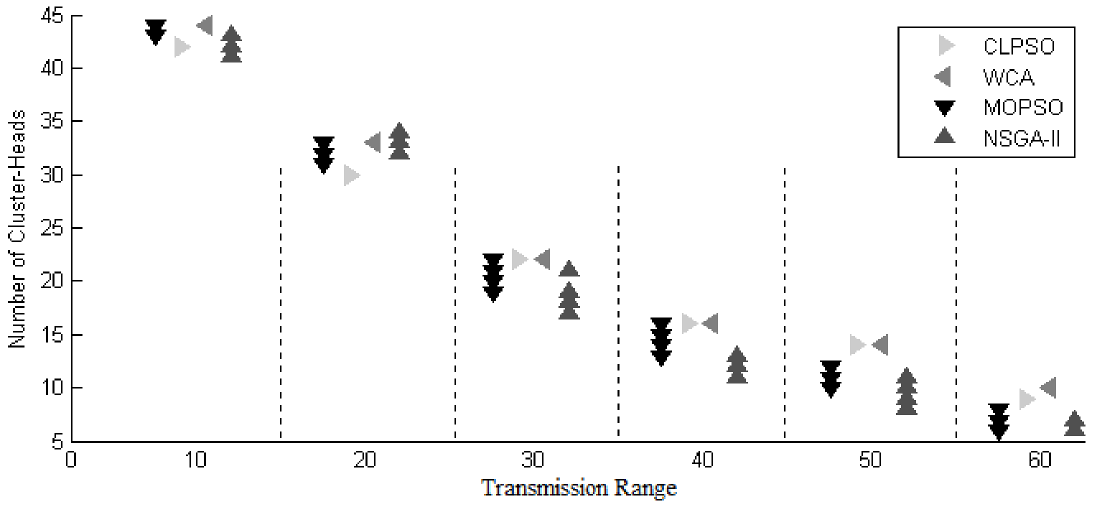
In addition, the numerical results indicate that expansion of the network area is not affecting the efficiency of the proposed approach and it performs efficiently in both cases.

The performance of the proposed method is further investigated through changing the number of nodes available in the network from 20 to 60 nodes. The experiment is repeated for two different sizes of the network area. The numerical results signifies that the proposed algorithm generally presents better results, smaller number of cluster heads, when it is compared to WCA, CLPSO and MOPSO. It can be observed that in both cases when the number of nodes in the network is the minimum of its range (20), both MOPSO and NSGA-II present a single final solution as their Pareto-optimal set though they are able to generate multiple solutions when the number of sensor nodes increase.

The same experiment is carried out considering different transmission ranges and network area and the results are presented in Figures 6 and 7. The results once again prove that the proposed approach can generate better final solutions comparing to the existing methods. Moreover, with the exception of the case when there exists 20 sensor nodes in the network, NSGA-II presents a set of final solutions and therefore gives the flexibility for the design of the network.



(a)



(b)

Figure4. The effect of the transmission range on the number of clusters by CLPSO, WCA, MOPSO, and NSGA-II in a 300 m × 300 m area and the number nodes is 40 and 50 in (a) and (b) respectively.

5.2.3 The effect of grid size

Figure 7 illustrates the relation of the number of cluster heads and the dimension of implementation environment.

As it is obvious, the increase in the dimension of the implementation environment leads to the increase of the number of cluster heads. The obtained results show that the results of the proposed method are entirely better than those of CLPSO and WCA methods while its results in comparison with MOPSO method is relatively better.

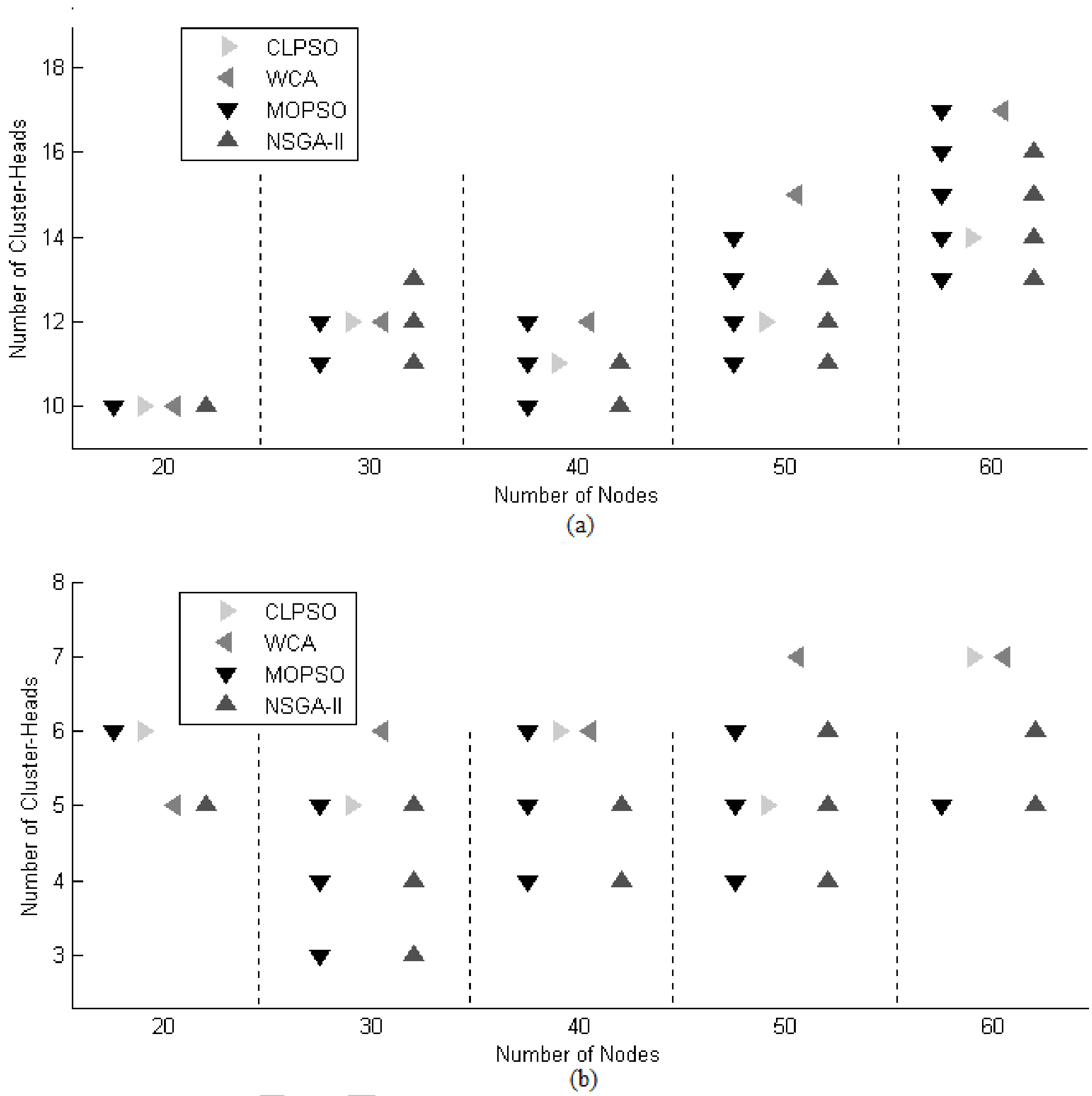


Figure5. The variation of the number of cluster-heads by the number of network nodes by WCA, CLPSO, MOPSO, and NSGA-II methods in a 100 m × 100 m area for a transmission range of 20 and 40 in (a) and (b) respectively

5.2.4 Energy consumption

The first order radio model, the same as [37], is used in the experiments; in this model $E_{elec} = 50\ nJ/bit$ and $E_{amp} = 100\ pJ/bit/m^2$ are used to run the transmitter-receiver circuitry and amplifier respectively. These power levels are suitable for E_b/N_0. The energy consumption of a node is proportionate to the square of the distance between the transmitter and receiver nodes. Hence, the total energy required for sending an n-bit message is determined as follows.

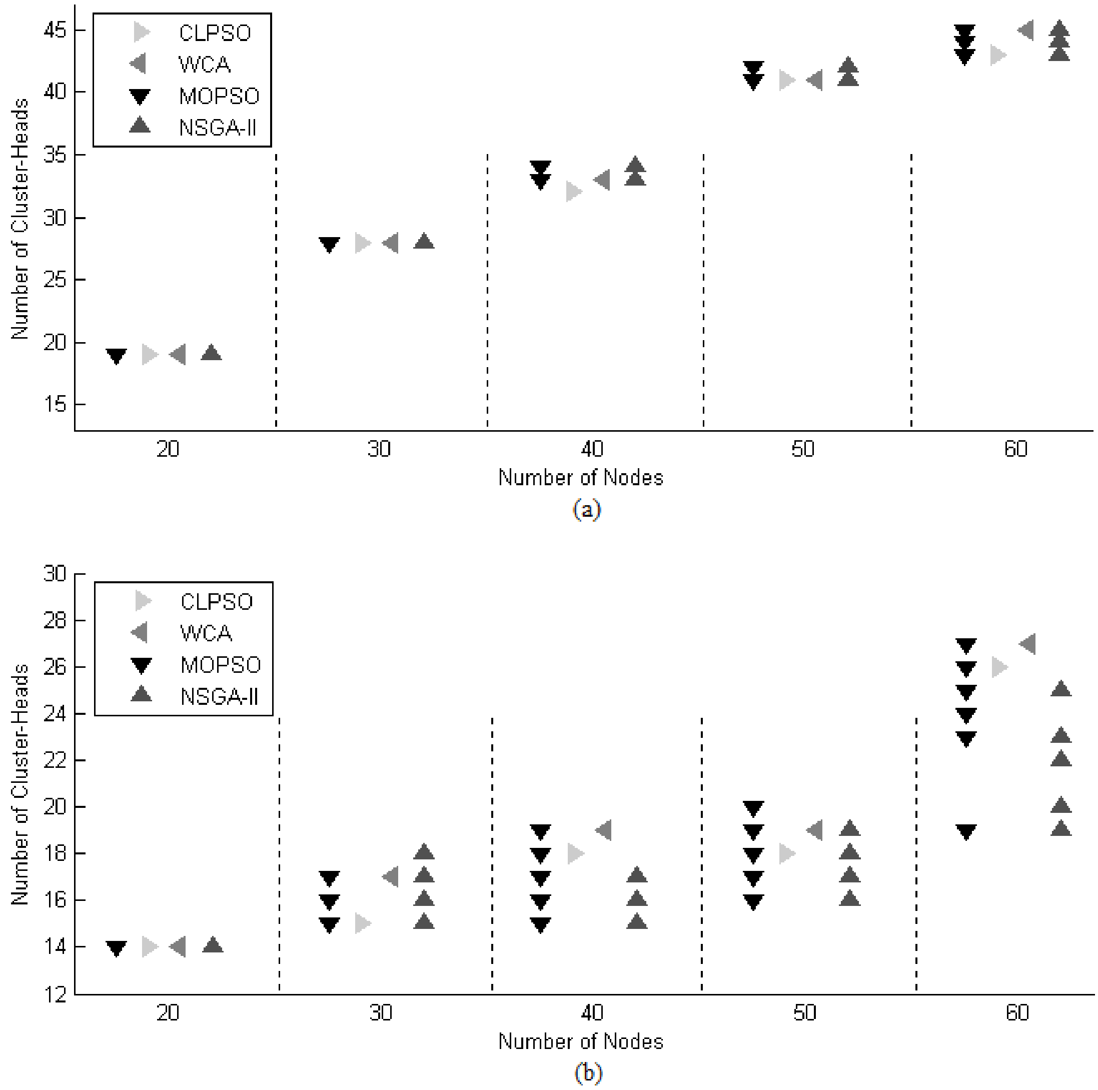


Figure6.The variation of the number of cluster-heads by the number of network nodes by WCA, CLPSO, MOPSO, and NSGA-II methods in a 200 m × 200 m area for a transmission range of 10 and 30 in (a) and (b) respectively

The necessary energy of a receiver node= the consumed energy in circuitry + the consumed energy for a transmitter to send an n-bit message to the receiver

$$E_T(n \cdot d) = E_{TX}(n \cdot d) + E_{RX}(n \cdot d) \quad (4)$$

Where

$$E_{TX}(n \cdot d) = E_{elec} \times n + E_{amp} \times n \times d^2 \quad (5)$$

and

$$E_{RX}(n \cdot d) = E_{elec} \times n \quad (6)$$

Considering Equations (5) and (6), energy consumption is dependent on the transmitter and receiver nodes distance. For the purpose of this test, 30 sensors are randomly distributed in a 100 × 100 area. Then, the receiver sensor is placed at the point (50,110).

Figure 8 shows the obtained results for energy consumption by CLPSO, WCA, MOPSO and NSGA-II. As can be seen the transmission range is increased, the more energy is consumed. In another test, energy consumption is measured while the previous set-up is maintained and sensors are increased to 40 and 60. The results are shown in Table 4.

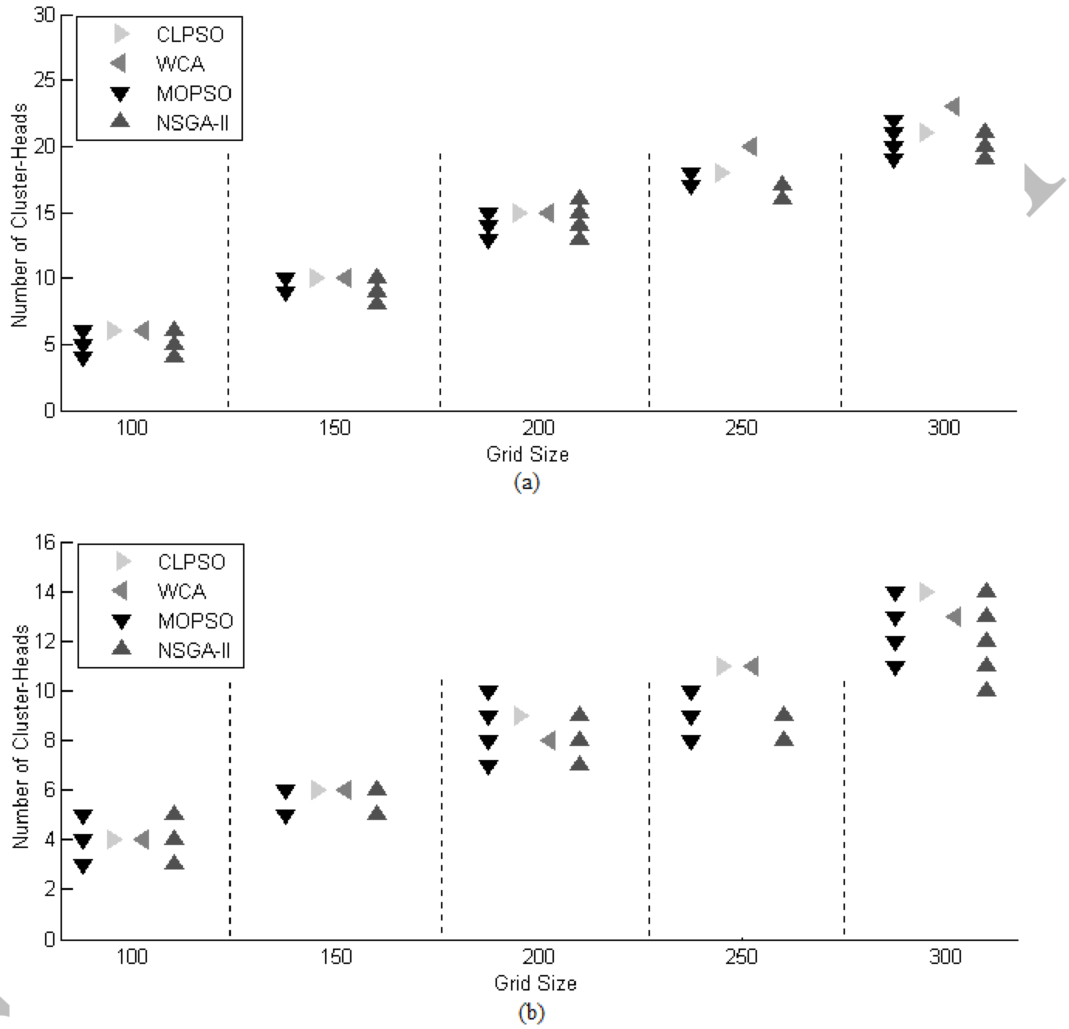


Figure 7. The effect of grid size on the number of cluster-heads by WCA, CLPSO, MOPSO, and NSGA-II methods when the number of nodes = 40 and transmission range is fixed to 40 and 50 for (a) and (b) respectively

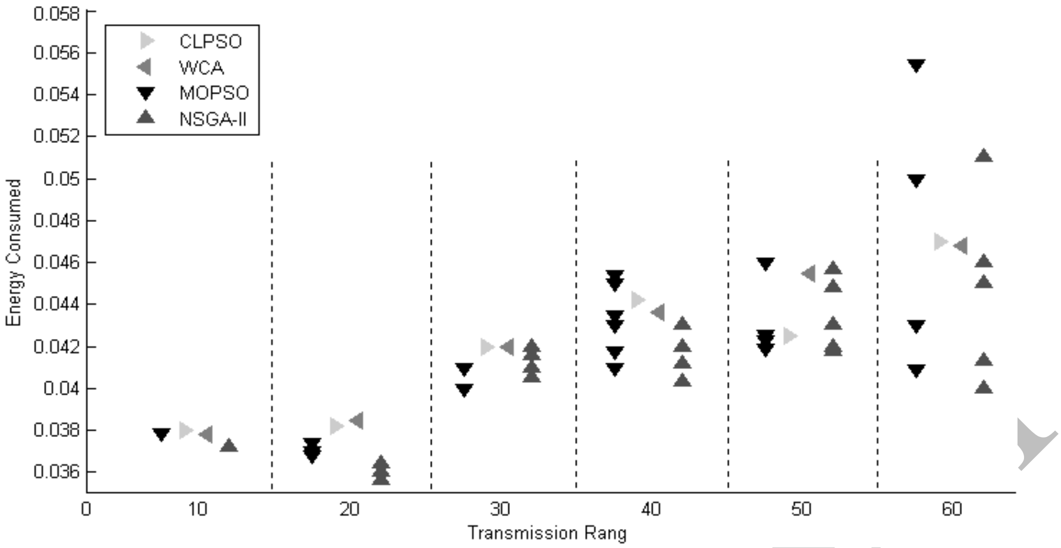


Figure8. Level of energy consumption by WCA, CLPSO, MOPSO, and NSGA-II methods for a 100 m × 100 m area, the transmission range varying from 10 to 60 and the number of nodes=30.

Table4. Energy consumed by different algorithm when nodes= 40 and 60

	CLPSO		WCA		MOPSO		NSGA-II	
	No. of sensors		No. of sensors		No. of sensors		No. of sensors	
Transmission Rang	40	60	40	60	40	60	40	60
10	0.0571	0.0823	0.0568	0.0816	0.0563	0.0811	0.0553	0.0814
20	0.0623	0.0894	0.0572	0.0881	0.0591	0.0837	0.0586	0.0833
30	0.0631	0.0928	0.0638	0.0977	0.0513	0.0872	0.0534	0.0887
40	0.0634	0.0981	0.0569	0.0908	0.0576	0.0844	0.0572	0.0831
50	0.0718	0.0976	0.0743	0.103	0.0573	0.107	0.0579	0.0972
60	0.0779	0.0980	0.0742	0.139	0.0538	0.0817	0.0537	0.0823

6. Conclusions

In the present article, a new method for finding the number of optimum cluster heads within an Ad-hoc sensor network is presented using to the Fast and Elitist Multi Objective Genetic Algorithm (NSGA-II).

Considering four different objectives, namely energy consumption, the number of cluster heads, the amount of coverage, and degree difference, the proposed method determines the optimal Pareto-front for a specific network. One of the distinctive advantages of the proposed method is the application of Non-Dominancy and Pareto Optimality concepts for finding several optimum solutions at each step. Optimum solutions are determined so that they could relatively meet the requirements of objectives. Maintaining the situations equal, the proposed method is compared with CLPSO, WCA, and MOPSO methods. The results (which are presented in Section 5) indicate the effectiveness of the proposed method in comparison with other common methods in this field.

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