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Maximizing lifetime of large-scale wireless sensor networks using multi-objective whale optimization algorithm

Mohammed M. Ahmed[1,3] · Essam H. Houssein[1,3] · Aboul Ella Hassanien[2,3] · Ayman Taha[2] · Ehab Hassanien[2]

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Abstract

The sink nodes in large-scale wireless sensor networks (LSWSNs) are responsible for receiving and processing the collected data from sensor nodes. Identifying the locations of sink nodes in LSWSNs play a vital role in term of saving energy. Furthermore, sink nodes have extremely extra resources such as large memory, powerful batteries, long-range antenna, etc. This paper proposes a multi-objective whale optimization algorithm (MOWOA) to determine the lowest number of sink nodes that cover the whole network. The major aim of MOWOA is to reduce the energy consumption and prolongs the lifetime of LSWSNs. To achieve these objectives, a fitness function has been formulated to decrease energy consumption and maximize the network's lifetime. The experimental results revealed that the proposed MOWOA achieved a better efficiency in reducing the total power consumption by 26% compared with four well-known optimization algorithms: multi-objective grasshopper optimization algorithm, multi-objective salp swarm algorithm, multi-objective gray wolf optimization, multi-objective particle swarm optimization over all networks sizes.

Keywords Large-scale wireless sensor networks (LSWSNs) · Multiple sink node · Multi-objective optimization (MOO) · Pareto front · Whale optimization algorithm (WOA)

1 Introduction

Wireless sensor networks (WSN) contains many devices called sensor nodes and large-scale wireless sensor networks (LSWSNs) are composed of a huge number of sensor nodes that consist of, storage resources, transceivers, possible actuators, and processing [1]. WSNs have many applications such as seismic stations, civil, battlefield surveillance, health monitoring, habitat monitoring, home automation, and traffic control. Wireless sensor networks are deployed in the earthquake region to monitor and remotely track seismic wave that occurred in specific region [2] through designing the locations of seismic sensing stations.

The strategy of choosing the optimal location of the sink node will decrease the energy consumption via decreasing the distance between sensor nodes and sink nodes thus, the network's lifetime increases [3,4]. Consequently, choosing many sink nodes locations is regarding as an multi-objective optimization problem that considered one of the major challenges in LSWSNs. The Whale Optimization Algorithm (WOA) was proposed recently and WOA has a special mechanism that balances between the exploration and exploitation phases. In order to maximize network's lifetime, this paper proposes a Multi-objective Whale Optimization Algorithm (MOWOA) for selecting the optimal location of sink nodes in LSWSNs either to reduce transmitting data time from the sensor node to sink or to optimize energy-efficiency to maximize network's lifetime. several studies have been proposed in the literature deal with the multi-objective optimization problems such as; Particle Swarm Optimization (PSO) [5] and Genetic Algorithm (GA) [6] that used to find the Pareto optimal front that represents Pareto optimal (PO) solutions [7,8].

✉ Mohammed M. Ahmed
Mohmed.mostafa111@yahoo.com
http://www.egyptscience.net

Essam H. Houssein
http://www.egyptscience.net

Aboul Ella Hassanien
http://www.egyptscience.net

1 Faculty of Computers and Information, Minia University, Minya, Egypt

2 Faculty of Computers and Information, Cairo University, Giza, Egypt

3 Scientific Research Group in Egypt (SRGE), Giza, Egypt

Therefore, the proposed MOWOA is aim to choose the best Pareto front that contains non-dominated solutions. Non-Dominant solutions (best positions) is used to guide the whales called a leader. In each iteration, an external archive stores the non-dominant solutions [9]. The proposed MOWOA have some of the merits such as; evaluating the fitness functions, selecting the leaders from the external archive to promote diversity in the external archive and maintaining the external archive. The neighborhood topology used for information exchange. On the other hand, the major aim of MOWOA is to decrease the distances between the sink nodes and the remnant sensor nodes in LSWSNs and efficiently reduce power consumption of the sensor nodes that are the farthest from sink node.

The structure of this paper is organized as follows. In Sect. 2 the related work is introduced. Section 3 presents an overview of the problem description and the multi-objective optimization problem. Section 4 briefly, introduces the concepts of whale optimization algorithm and the proposed MOWOA. The performance evaluation of the proposed algorithm with the existing algorithms is presented in Sect. 5. Conclusions are presented in Sect. 6.

2 Literature review

Even though the sink node location is an obvious problem in WSNs and LSWSNs, the literature has been dealt with sink node location rarely compared to other areas. Although, many studies such as, [10] introduced an algorithm for multiple sink node design network in LSWSNs which claim that choose best of multiple sink nodes locations. Also, [11] proposed a multiple sink nodes location method in WSN and transmission path from all sensors to these multiple sink nodes.

The literature review focuses on data mining techniques and swarms optimization that consists of single objective and multi-objective, in Table 1 shows some of the key findings from the literature review of related works.

Firstly, data mining based taxonomy for single and multi-objective such as in [12], Heinzelman et al. presented the Low-energy adaptive clustering hierarchy that is called (LEACH) to enable the rotating cluster head positions and self-organization of huge numbers of nodes in WSNs that solve energy constrained. Peiravi [14] proposed multi-objective genetic algorithm based clustering that reduces the total communication distance to improve the network's lifetime. In [13] proposed an algorithm to optimize K-Nearest Neighbor (KNN) to choose best k number of neighbors for the sink node that is determined via whale optimization algorithm. Another work proposed algorithm in [22] that balances between clusters in multiple base stations for small to medium scale WSNs.

And swarm optimization based taxonomy composed of the single and multi-objective swarm optimization algorithm. In regards of the node localization, the determination of sink node location in a small WSNs based on cat swarm optimization algorithm (CSO) was proposed in [16] and compared with particle swarm optimization (PSO) in [18]. In [17] proposed binary version from single objective swarm is called whale optimization algorithm, that choose the best number of active nodes, inactive node and it's locations in the network but ensure all network is covering using breadth-first search to maximize the network's lifetime. Further, bee algorithm with simulated annealing for a weighted minimum spanning tree (BASA-WMST) was proposed in [19]. While the bee algorithm responsible for information exchange within the network, the simulating annealing is the escaping algorithm from sticking in local optima. Through a comparison between the BASA-WMST and other bio-inspired based algorithms, it shows a significant performance improvement that goes linearly with the networks size expansions.

Many of multi-objective swarm algorithms [23,24] have proposed in the literature such as multi-objective bee colony algorithm [21]. Greedy simulated annealing is utilized to optimize the sink node location [25]. Rani and Devarajan in [20] proposed multi-objective PSO with fuzzy logic (FL) to solve Sensor node location problem to choose the best of the non-dominated solutions that are in the Pareto front [26]. Some researchers have proposed a sink node location strategies such as Chen and Li [27] which combine the energy and lifetime in both multiple-hop and single-hop WSNs. Also, in [28] a multi objective clustering for wireless sensor networks have presented.

Furthermore, an overview of theory and methods of evolutionary multi-objective optimization are presented in [29], That clarify basic principles of multi-objective optimization and evolutionary algorithms [30,31]. Multi-objective deployment of wireless sensor nodes has been surveyed in [32] to achieve Pareto optimal front while considering multiple

Table 1 Literature review taxonomy

Taxonomy	Single objective	Multi-objective
Data mining	LEACH [12], WOA-KNN [13]	MOGA clustering[14], MCPSO[15]
Swarm optimization	CSO [16], WOTC [17], PSO [18], BASA-WMST [19]	MOPSO [20], MOBCA [21]

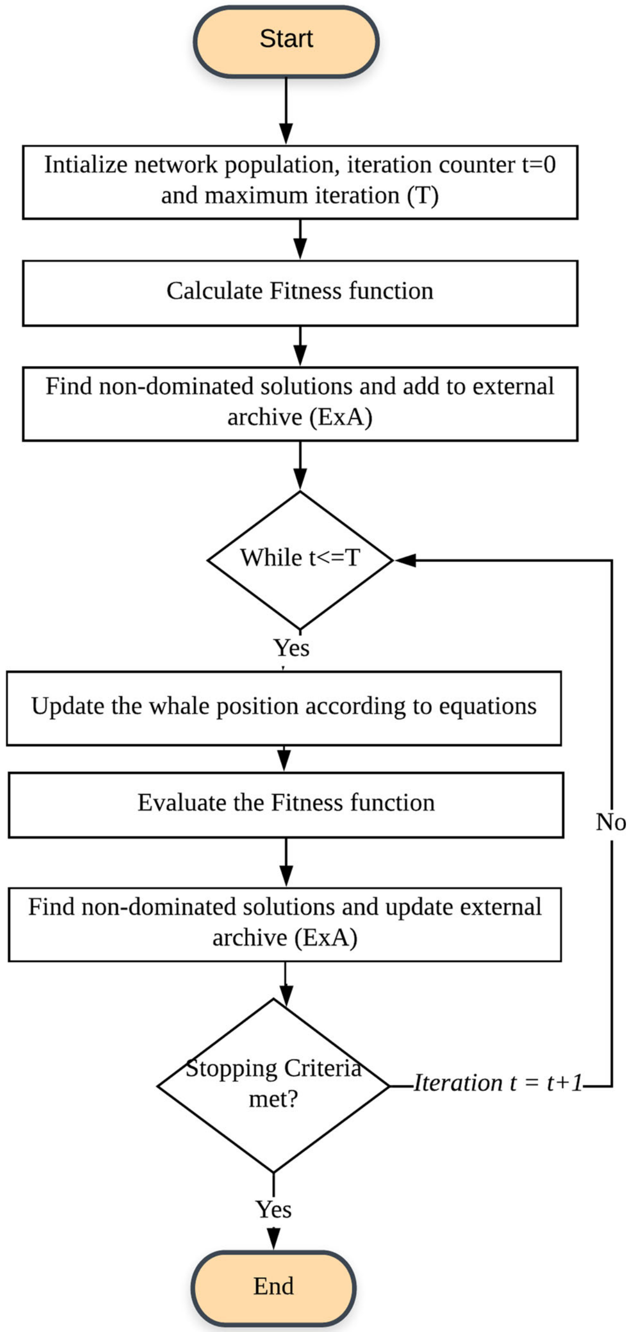


Fig. 1 The architecture of the proposed MOWOA

conflicting objectives namely, coverage, energy efficiency, lifetime and the number of sensors. Also, an updated review of multi-objective optimization techniques being used to solve different problems relating to the design, operation, deployment, placement, planning, and management of sensor networks is presented in [33]. Abidin et al. [34,35] proposed Territorial Predator Scent Marking Algorithm (TPSMA) to choose optimal location for sensors in WSN to achieve low energy consumption with guaranteed connectivity. In [36] proposed IADLoc that called Improved Accuracy Distribution localization for wireless sensor networks which used to minimize energy consumption without any additional hardware cost through signals from the sensor node and sink node.

In addition to those above, most researchers focused on the energy conservation like [37], and several studies like [38] allocating multiple sink nodes locations in LSWSNs and the location of sensor nodes in multi-hop wireless networks is optimized. Finally, up to our knowledge, all the techniques that have been presented to deal with the sink node location for WSNs and especially for LSWSNs are regarded this problem as a single objective (single fitness function).

Hence, these techniques either fail to incorporate several specific application requirements into the performance evaluation or suffer from limited objectives. This is the motivation of this study, another point of view to deal with optimal locations of sink node in LSWSNs as a multi-objective problem in which an effective algorithm is proposed called MOWOA and based on WOA methodology. The contribution of this paper are:

1. Finding optimal locations of sink nodes in LSWSNs.
2. Reducing distances from sensor nodes into sink nodes in a network to avoid extreme data transmission.
3. Saving the energy consumption.

3 Methodology

3.1 Problem formulation

LSWSNs consists of thousands number sensor nodes, and these nodes are deployed uniformly in a specific region area $R = L \times L$, where L represents the length of the area side. there is two restricted method for sensor nodes that are memory and bandwidth. The sensor nodes can receive messages and distribute to the sink nodes. In LSWSNs, each sensor nodes transmit messages to the sink node that represents the bottleneck and one of the major constraints in LSWSNs, and hence this limits the performance and lifetime of the network. In this paper, the whole network area is divided into some sub-networks, which makes the cluster distribution uniform to decrease the energy consumption, the farther distance between cluster head and rest of nodes will make the inter-cluster head nodes consume more energy. Dividing the entire WSN into some regions with each region assigning with a cluster head so that the communication consumption between the members of the cluster and the cluster nodes can be maintained at a low level.

The main objective of LSWSNs design prolongs the network lifetime through placing sink nodes in an optimal location to decreases the distance of sensor nodes from its

Algorithm 1 The proposed MOWOA algorithm.

Input: A graph represents the nodes with energies divided into clusters using LEACH
Output: Sink nodes locations
Initialize the whales population X_i, $(i = 1, 2, \ldots, n)$.
Initialize A, p, C, a and l.
Calculate the fitness function.
Find pareto optimal solutions and external archive is initialized.
Initializing start of iteration $t = 1$ and initialize Maximum of iteration T.
while $t <= T$ **do**
  for all search agents do **do**
    if $p < 0.5$ **then**
      if $(|A| < 1)$ **then**
        Update node location by Eq.7
      else$(|A| \geq 1)$
        Select a random search agent (X_{rand})
        Update node location by Eq.15
      end if
    else$(p \geq 0.5)$
      Update current node location by Eq.11
    end if
    Update A, p, C, a and l.
    Calculate the fitness function for each search agent
    Obtain non-dominated solutions and Update external archive (ExA).
    if external archive (ExA) is full **then**
      omit one solution from the archive.
      Add the new solution to external archive (ExA)
    end if
  end for
  t=t+1
end while
return ExA that contains sink nodes locations.

neighbor's sink with low energy consumption. Cluster-based schemes improve network lifetime; however, most popular algorithms of clustering such as LEACH, k-means use the concept of one hop for intra-cluster which leads to the larger average transmission distance. In this paper, MOWOA-based cluster formation technique with multiple objectives is proposed for intra-cluster data aggregation with a connected dominated set (CDS). Multiple sink node is regarded as one of the possible solutions for LSWSNs to decrease the distance between the nearest sink node and each sensor node to save the energy consumption for transmission data operations.

3.2 Multi-objective optimization

Many optimization problems are naturally multi-objective that usually have more than one objective functions which in conflict with each other. Multi-objective optimization (MOO) created to overcome some conflicting objectives simultaneously. In multi-objective optimization, there are some solutions, but none of them can be said the winner. Therefore, the aim from the external archive is to store the non-dominated solutions. In the initialization phase, the external archive is constructed. Then, all obtained solution are rearranged according to non-domination compared with each other in the space to choose the non-dominated solution. Finally, all non-domination solution is stored in the external archive.

The major task of MOO is to find a trade-off between the conflicting objectives and the results of MOO are a set of solutions. The point $\overrightarrow{X}' \in \Omega$ is an optimal of Pareto if, for all $\overrightarrow{X} \in \Omega$ and $g = 1, 2, \ldots, k$ either,

$$\forall \mathrm{i}\ \mathrm{g}(f_i(\overrightarrow{X}) = f_i(\overrightarrow{X}')),$$

or i ∈ g such that:

$$f_i(\overrightarrow{X}) \geq f_i(\overrightarrow{X}')$$

Finding the vector $\overrightarrow{X}' = [x'_1, x'_2, \ldots, x'_n]^T$ that satisfies the n inequality constraints: $q_i(\overrightarrow{X}) \geq 0\ i = 1, 2, 3 \ldots, n$ and the equality constraints $w_i(\overrightarrow{X}) = 0\ \ i = 1, 2, \ldots, p$ and improves.

$$\overrightarrow{f}(\overrightarrow{X}) = [f_1(\overrightarrow{X}), f_2(\overrightarrow{X}), f_3(\overrightarrow{X}) \ldots, f_k(\overrightarrow{X})]^T$$

MOO problem is divided into many of single objectives that they are optimized concurrently. Whale optimization algorithm (WOA) was adapted to present a new version called the multi-objective whale optimization algorithm (MOWOA). In order to achieve that, non-dominated Pareto optimal solutions are applied [39]. As well as the multi-criterion metrics, the following criteria are satisfied when a non-dominated solution is considered an optimal solution.

1. *Pareto dominance* $V = (v_1, v_2, \ldots, v_n)$ and $U = (u_1, u_2, \ldots, u_n)$ are a given two vectors. U dominates V if and only if U is partially less than V in the objective space as follows:

$$\begin{cases} f_i(U) \leq f_i(V) & \forall\, i\ ,\ i = 1, 2, \ldots, m, \\ f_i(U) < f_i(V) & \exists\, i \end{cases} \tag{1}$$

Table 2 Various parameters used in the simulation

Parameter	Value
Deployment area	1000 m × 1000 m
Routing protocols	LEACH
Number of nodes	1000, 2000, …, 10,000
Sensor node model	Mica Mote
Node communication	Range 100 m
Node sensing	Range 20 m
Node placement	Uniform
Node energy	Uniform
Max energy	2000 (mA-h)

Table 3 Parameter settings of experiments for each different algorithms

MOWOA	MOGOA	MSSA	MOGWO	MOPSO
a = 0.7	$c_{min} = 0.001$	$c_1 = 0.7$	a = 0.8	$c_1 = 2.05$
r = 0.9	$c_{max} = 1$	$c_2 = 0.6$	$r_1 = 0.6$	$c_2 = 2.05$
k = 0.4	l = 1.2	$c_3 = 0.5$	$r_2 = 0.6$	w = 0.729
b = 0.6	f = 0.5	$v_0 = 0$		$r_1 = 0.9, r_2 = 0.4$

Table 4 The detailed settings

Name	Detailed settings
Software	
Operating system	Windows 10
Language	MATLAB R2015a
Hardware	
Processor	Core(TM) i7-4500
Frequency	2.40 GHz
Memory	8G
Hard disk	500 GB

where the number of fitness functions represented by m.

2. *Pareto optimal solution* PO represented by U if and only if any other obtained solutions cannot dominate U.

Pareto Optimal Front $PF_{Optimal}$ is consist of group Pareto optimal solutions and it contains a group of non-dominated solutions.

For fair comparisons among the proposed MOWOA and the compared algorithms, in this paper, to evaluate meta-heuristic algorithms performance via four assessment measures. Every measure details are illustrated below.

Metric of spread Deb [6] proposed the spread metric (Δ), to determine the propagation of spread achieved via the non-dominated solutions, the spread metric (Δ) formulated as below:

$$\Delta = \frac{d_f + d_l + \sum_{i=1}^{n_{pf}} |d_i - \hat{d}|}{d_f + d_l + (n_{pf} - 1)\hat{d}} \tag{2}$$

where d_f and d_l are considered the Euclidean distances between the extreme solutions in $PF_{Optimal}$ and PF, respectively, d_i indicates the Euclidean distance between each point in PF and the closest point in $PF_{Optimal}$, the total number of members in PF represented by n_{pf}, and the average of all distances represented by $\hat{d}$. As formulated in Eq. 2.

Metric of spacing is considered the non-dominated solutions distribution and is clarify as follows:

$$MS = \sqrt{\frac{1}{n_{pf} - 1} \sum_{i=1}^{n_{pf}} (d_i - \hat{d})^2} \tag{3}$$

The metric of spacing represented by MS, the Euclidean distance between the ith member in PF and nearest member in PF represented by d_i, PF is the generated Pareto front, and all distances average is $\hat{d}$. The Euclidean distance is clarify in Eq. 4.

$$d(a, b) = d(b, a) = \sqrt{\sum_{i=1}^{n} (f_{ia} - f_{ib})^2} \tag{4}$$

where $a = (f_{1a}, f_{2a}, f_{3a}, \ldots, f_{na})$ and $b = (f_{1b}, f_{2b}, f_{3b}, \ldots, f_{nb})$ are considered two points on the PF.

Generational Distance Veldhuizen and Lamont [40] proposed the generational distance (GD) metric. GD measure is defined as follows:

$$GD = \frac{1}{n_{pf}} \sqrt{\sum_{i=1}^{n_{pf}} d_i^2} \tag{5}$$

where members in the obtained Pareto front PF represented by n_{pf} and d_i represents the distance between ith member in PF and the nearest member in $PF_{Optimal}$.

Inverted Generational Distance IGD is modified by Sierra and Coello [41] as follows:

$$IGD = \frac{\sqrt{\sum_{i=1}^{n} d_i^2}}{n} \tag{6}$$

The true Pareto optimal solutions is indicated by n, the Euclidean distance between n and non-dominated solutions.

3.3 Whale Optimization Algorithm

Whale Optimization Algorithm (WOA) was proposed by Mirjalili et al. [42], and mathematically has been modeled as follows:

3.3.1 Bubble-net attacking method

WOA is mimicking to the humpback whales behavior. Mathematically the spiral updating position methods and shrinking encircling are defined as below:

Shrinking encircling The prey is formulated as the best candidate solution and residue agents aim to choose their

Table 5 Running time for the different algorithms per second

N	MOWOA (s)	MOGOA (s)	MSSA (s)	MOGWO (s)	MOPSO (s)
1000	98.425	549.213	323.819	147.638	221.456
2000	367.879	1183.940	775.909	551.819	827.728
3000	736.536	1868.268	1302.402	1104.804	1657.206
4000	1824.024	2912.012	2368.018	2736.036	4104.054
5000	2529.243	3768.622	3146.932	3793.865	5690.797
6000	3412.681	4706.341	4059.511	5119.022	7678.532
7000	4837.332	5918.666	5377.999	7255.998	10,883.997
8000	5678.148	6839.074	6258.611	8517.222	12,775.833
9000	7123.687	8061.844	7592.765	10,685.531	16,028.296
10,000	8724.982	9362.491	9043.737	13,087.473	19,631.210

positions according to it as illustrated in the following formulas:

$$\overrightarrow{X}(t+1) = \overrightarrow{X}(t) - A \cdot \overrightarrow{D} \tag{7}$$

$$\overrightarrow{D} = |C\overrightarrow{X}'(t) - \overrightarrow{X}(t)| \tag{8}$$

$$A = 2 \cdot a \cdot r - a \tag{9}$$

$$C = 2 \cdot r \tag{10}$$

where $\overrightarrow{X}$, $\overrightarrow{D}$, t, and r are illustrates the best solution, whale position, current iteration and a random number within [0, 1] respectively, parameter a decreases from 2 to 0 over with the number of iterations.

Spiral updating The relation between the prey' position and whale is calculated by the Eqs. 11 and 12 as follows:

$$\overrightarrow{X}(t+1) = e^{bk} \cdot cos(2\pi k) \cdot D' - \overrightarrow{X}'(t) \tag{11}$$

$$D' = |\overrightarrow{X'}(t) - \overrightarrow{X}(t)| \tag{12}$$

where b represents a constant, and k represents a random number within [− 1, 1].

The mathematical model is as follows when the probability of 50% is chosen for the spiral-shaped path or a shrinking circle.

$$\overrightarrow{X}(t+1) = \begin{cases} \overrightarrow{X'}(t) - \overrightarrow{A} \cdot \overrightarrow{D} & if\ p \prec 0.5 \\ \overrightarrow{X'} \cdot e^{bl} \cdot \cos(2\Pi l) + \overrightarrow{X'}(t) & if\ p \geq 0.5 \end{cases} \tag{13}$$

where p represents a random value within [0, 1].

3.3.2 Search for prey

A search agent position is chosen randomly. To update the search agent randomly and avoiding the local optima that calculated as follows:

$$\overrightarrow{D''} = |C.\overrightarrow{X(t)}_{rand} - \overrightarrow{X}(t)| \tag{14}$$

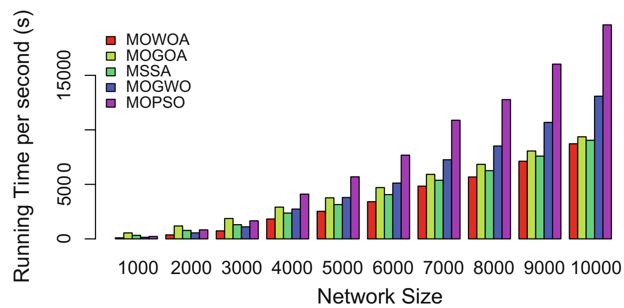


Fig. 2 Running time for algorithms MOWOA, MOGOA, MSSA, MOGWO and MOPSO for network 2000 nodes

$$\overrightarrow{X}(t+1) = \overrightarrow{X(t)}_{rand} - A.\overrightarrow{D''}| \tag{15}$$

where $\overrightarrow{X(t)}_{rand}$ is generated randomly according to the following two conditions; $|A| > 1$ and $|A| < 1$.

4 The proposed maximizing lifetime of large-scale wireless sensor networks

Many real-life optimization problems are regarded as multiple objectives, and one of the big challenges is to be optimized and obtaining the best solution easily. So, diversity techniques have been developed to tackle with this kind of problems. Furthermore, nature-inspired optimization algorithms that find approximate solutions have attracted great interest over the last decades. Also, several studies have been introduced to solve the multi-objective problems such as MOGOA [43], MSSA [44], MOGWO [45], MOPSO [46].

A multi-objective version based on WOA called MOWOA was introduced here to solve the multi-objective problem. WOA is a "population-based algorithm" and hence each whale is considered a solution in the multi-dimensional space. Also, the previous best experience for each whale has recorded in the external archive and each whale must know the obtained leader solution by the whole swarm. Finally,

Table 6 Experimental results obtained from fitness function for the proposed algorithm MOWOA versus MOGOA, MSSA, MOGWO and MOPSO algorithms

N	CP	MOWOA	MOGOA	MSSA	MOGWO	MOPSO
1000	SN	10	11	11	12	14
	EC	8958	13,865	12,741	13,025	14,199
2000	SN	7	12	10	11	10
	EC	7301	10,223	10,223	9796	11,955
3000	SN	7	10	8	10	9
	EC	7512	10,213	9952	11,547	8718
4000	SN	5	9	8	6	6
	EC	4186	5650	7826	4741	4997
5000	SN	6	7	9	7	7
	EC	5348	7203	8241	6892	6892
6000	SN	9	8	10	8	9
	EC	7520	9047	10,231	11,261	8342
7000	SN	10	9	10	9	8
	EC	8102	10,687	11,475	12,652	9730
8000	SN	8	12	11	7	10
	EC	7550	10,329	9663	11,970	9663
9000	SN	9	11	12	10	10
	EC	8541	9563	11,057	10,358	8621
10,000	SN	10	13	14	11	12
	EC	10,224	11,287	11,837	12,101	12,320

when the non-dominated solutions counting is exceeding over the allocated size of the external archive, so the crowded members are removed using the crowding distance [47].

An external archive saves the non-dominated solutions. The difference between the MOWOA and WOA is the target update process that guides the search agents towards promising areas of the problem space is considered as the major difference between the MOWOA and WOA. Equation 16 clarify the probability of selecting the goal (P_i) in the archive.

$$P_i = \frac{1}{N_i} \tag{16}$$

The number of solutions represented by N_i in the neighborhood of the ith solution. Based on P_i, to select the goal from the archive via a roulette wheel.

The archive has fixed size, If The archive size is increased, the computational cost will grow. And if The archive size is decreased, the issue will occur in the full archive. Crowded neighborhood solutions are removed using the crowding distance [47] to solve this issue. In MOWOA is able to find the Pareto optimal solutions and store them in the external archive. The architecture of the proposed MOWOA is depicted in Fig. 1 and the detailed MOWOA is illustrated in Algorithm 1.

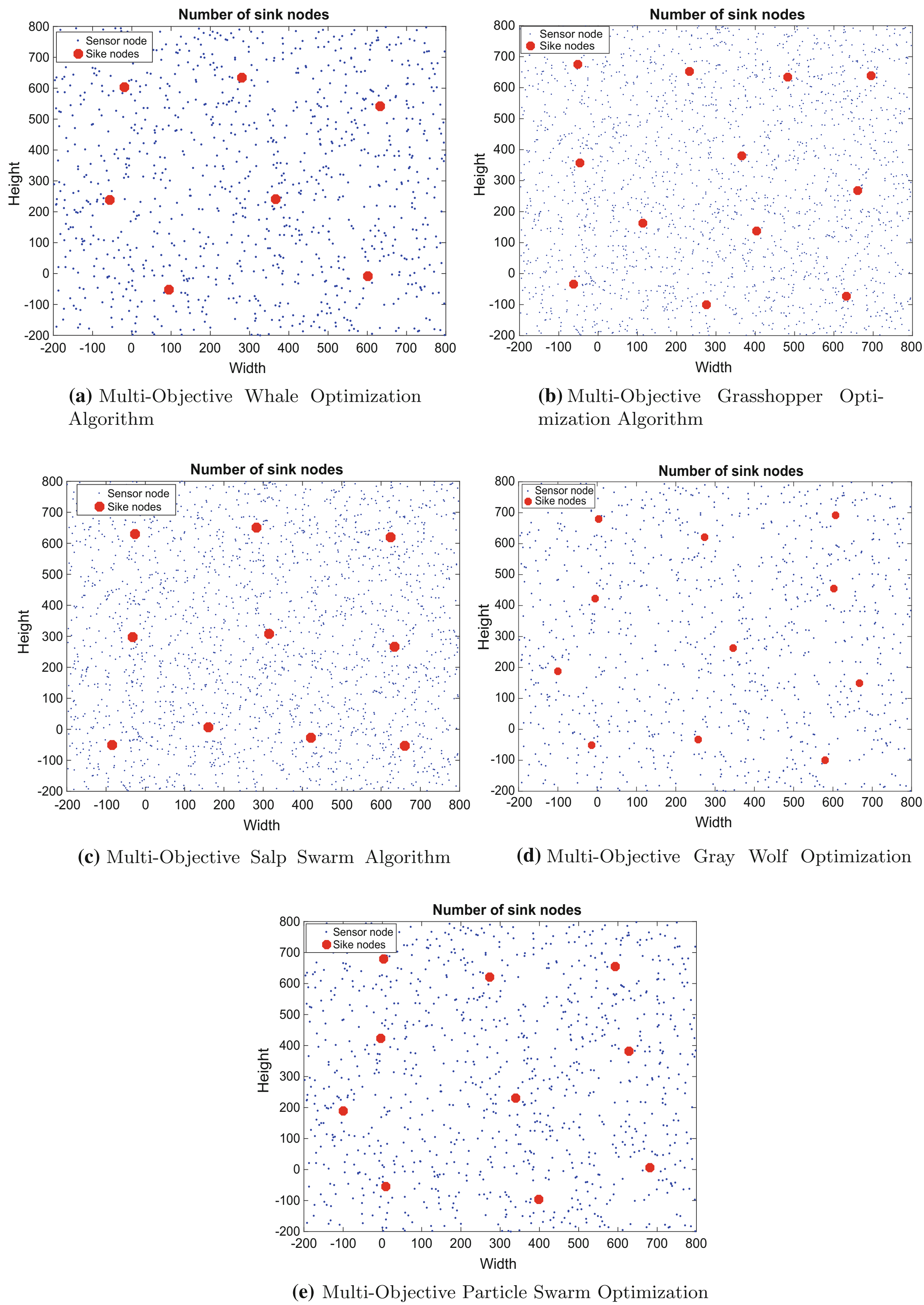
As aforementioned, this paper introduces a solution to the multi-objective optimization problem, where the fitness function is minimizing optimal sink node located in an LSWSNs and reducing energy consumption. WOA is adapted to accomplish the multi-objective optimization through two phases. In the first phase, an external archive is storing non-dominated solutions and the second phase depends on the strategy election of the leader which their task to select the whale leader solution from an external archive for the hunting process.

5 Experimental results and discussion

The results of the proposed algorithm reported in this section. MOWOA compared with MOGOA, MSSA, MOGWO, and MOPSO. The simulation parameters of the proposed algorithm are illustrated in Tables 2 and 3 clarifies parameter settings for each algorithm that used. The simulation nodes are supposed to mimic functions of Mica Mote sensors with energy model introduced in [48].

All the results are executed via the same PC that has the detailed settings as shown in Table 4.

The target from this experiment is to verify the proposed MOWOA algorithm and compare it with four algorithms MOGOA, MSSA, MOGWO, and MOPSO. In this experiment, in Table 5 depicts running time of proposed algorithm MOWOA is better than other algorithms MOGOA, MSSA, MOGWO, and MOPSO (Fig. 2).



(a) Multi-Objective Whale Optimization Algorithm

(b) Multi-Objective Grasshopper Optimization Algorithm

(c) Multi-Objective Salp Swarm Algorithm

(d) Multi-Objective Gray Wolf Optimization

(e) Multi-Objective Particle Swarm Optimization

Fig. 3 Sink node positions for network size 2000 nodes

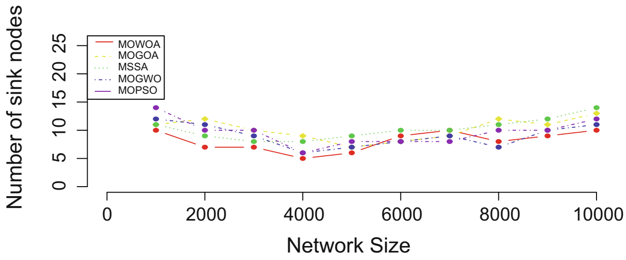


Fig. 4 Number of sink nodes for compared algorithms

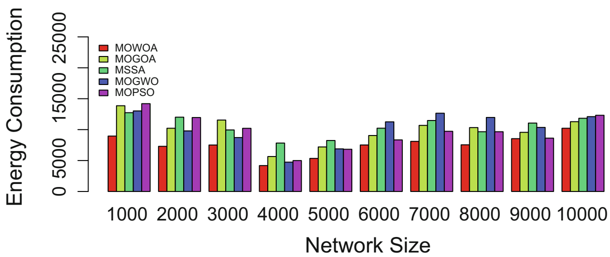


Fig. 5 Energy consumption for compared algorithms MOWOA, MOGOA, MSSA, MOGWO and MOPSO for network 2000 nodes

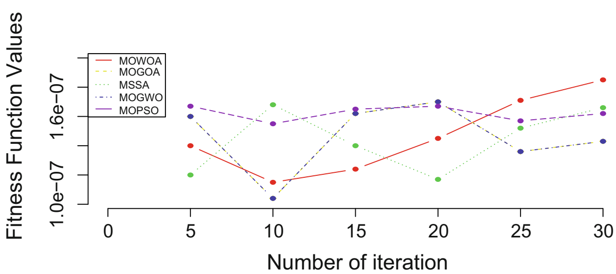


Fig. 6 The convergence of the fitness function

5.1 Fitness function

The performance of MOWOA evaluated via the number of sink nodes and energy consumption in four algorithms such as MOGOA, MSSA, MOGWO, and MOPSO are utilized. Equations 17 and 18 are utilized as the fitness functions of the proposed algorithm.

$$f_1(x) = \frac{AN}{N_{neighbor}} \tag{17}$$

$$f_2(x) = \frac{1}{\sum_{i=1}^{N_{neighbor}} E_{neighbor}} \tag{18}$$

where $N_{neighbor}$ denotes the number of sensor neighbor served by sink node, AN represents the number of active nodes, and $E_{neighbor}$ energy for each sensor node for sink's neighbors. The first fitness function $f_1(x)$ is the average of neighbor nodes and the second fitness function $f_2(x)$ is lower sum of energy per groups of nodes around sink node that selected. Both fitness function are dependent on the position vector x of all nodes. The localization optimization can be formulated as: $minf(x) = (f_1(x); f_2(x))$.

5.2 Results and discussion

All obtained results summarize in Table 6, where N, CP, SN, and EC means the network size, comparison parameters, sink nodes and energy consumption respectively.

Frequently, the techniques in the literature are utilized medium size WSN (typically less than 100 nodes) to evaluate these techniques. The proposed MOWOA is deployed in LSWSNs according to the fitness function. To test the cardinality of sink nodes of the proposed algorithm, 30 iterations were tested on the same network.

Figure 3a–e demonstrates the best cardinality of sink nodes have been obtained from MOWOA, MOGOA, MSSA, MOGWO and MOPSO respectively. Due to lack of space, we only included network size 2000 nodes only and the red points represent the location of sink nodes in the network.

Figure 4 shows the results the cardinality of the sink nodes curve from the proposed algorithm compare with other algorithms for LSWSNs. A shown in Fig. 4, the number of sink nodes obtained from the proposed algorithm have been balanced between network size and number of sink nodes through all networks sizes with low energy consumption compared with MOGOA, MSSA, MOGWO, and MOPSO algorithms.

Figure 5 represents the results of energy consumption obtained from the proposed algorithm MOWOA and other algorithms MOGOA, MSSA, MOGWO and MOPSO in all LSWSNs size. Also, Fig. 5, depicts the average energy consumption achieved by the proposed algorithm has been decreased by 26% compared to other algorithms. The fitness function convergence for compared algorithms depicts in Fig. 6.

Figure 7 displays the PF obtained by MOWOA with the fitness function for all network size. As shown, the fitness function has different Pareto fronts compared with other algorithms MOGOA, MSSA, MOGWO, and MOPSO. MOWOA provide the best convergence toward most of the true Pareto-optimal fronts. Generally, the proposed MOWOA algorithm proved the best results compared with the MOGOA, MSSA, MOGWO and MOPSO algorithms. In statistical results of inverted generational distance (IGD), generational distance (GD), metric of spread and metric of spacing. MOWOA achieved the best results than all the other algorithms in all network size. As shown in Tables 7 and 8.

As a summary, its clear from Figs. 4, 5 and 6 and Table 6, the proposed MOWOA has been achieved better results according to the number of sink nodes and energy consumption over all the network sizes compared to other existing algorithms. Also, the balance between a number of sink nodes

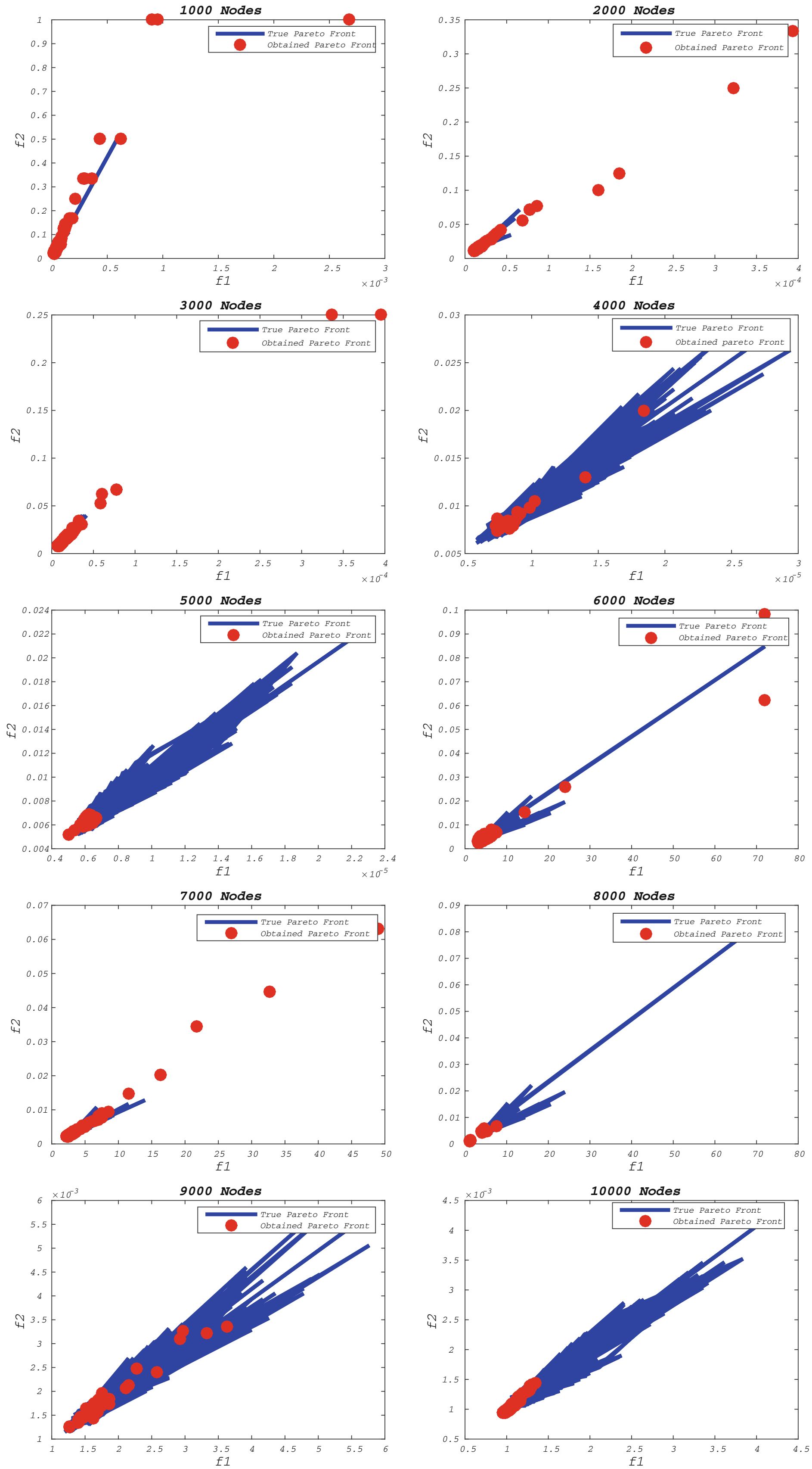


Fig. 7 Best Pareto optimal front obtained by MOWOA of fitness function scenario for network size 1000 through 10,000

Table 7 Results of the multi-objective algorithms on fitness function scenario for network size 1000 through 5000

Algorithm	GD		Metric of spread		Metric of spacing		IGD	
	Ave	Std	Ave	Std	Ave	Std	Ave	Std
1000 Nodes								
MOWOA	5.11E−01	7.22E−03	4.85E−03	7.03E−04	6.30E−04	2.53E−04	1.25E−02	1.13E−02
MOGOA	5.56E−01	8.17E−03	3.71E−02	3.64E−03	4.15E−02	1.88E−03	5.45E−01	6.40E−02
MSSA	6.03E−01	7.45E−03	3.32E−02	4.02E−03	4.73E−02	2.36E−03	3.48E−01	5.85E−02
MOGWO	5.33E−01	7.38E−03	3.68E−02	1.94E−03	4.23E−02	2.08E−03	8.42E−01	9.22E−02
MOPSO	5.30E−01	7.35E−03	4.97E−02	2.25E−03	3.10E−02	1.78E−03	6.17E−01	7.90E−02
2000 Nodes								
MOWOA	7.66E−01	1.08E−02	7.28E−03	1.06E−03	9.45E−04	3.80E−04	1.88E−02	1.69E−02
MOGOA	6.70E−01	2.42E−03	4.97E−02	2.98E−03	3.20E−02	1.78E−03	6.37E−01	7.40E−02
MSSA	5.47E−01	3.17E−03	3.04E−01	3.72E−02	3.76E−02	2.22E−02	6.03E−01	6.29E−02
MOGWO	8.00E−01	1.11E−02	5.51E−02	2.90E−03	6.34E−02	3.12E−03	1.26E+00	1.38E−01
MOPSO	7.95E−01	1.10E−02	7.46E−02	3.38E−03	4.65E−02	2.67E−03	9.26E−01	1.18E−01
3000 Nodes								
MOWOA	1.02E+00	1.44E−02	9.70E−03	1.41E−03	1.26E−03	5.07E−04	2.51E−02	2.25E−02
MOGOA	1.30E−01	1.35E−03	5.97E−02	6.25E−03	4.21E−02	2.38E−03	1.18E−01	1.90E−02
MSSA	2.30E−01	1.82E−03	4.18E−01	4.73E−03	5.08E−02	3.16E−03	2.24E−01	2.35E−02
MOGWO	1.07E+00	1.48E−02	7.35E−02	3.87E−03	8.46E−02	4.15E−03	1.68E+00	1.84E−01
MOPSO	1.06E+00	1.47E−02	9.95E−02	4.51E−03	6.20E−02	3.56E−03	1.23E+00	1.58E−01
4000 Nodes								
MOWOA	2.55E−01	3.61E−03	2.43E−03	3.52E−04	3.15E−04	1.27E−04	6.27E−03	5.63E−03
MOGOA	2.84E−01	3.75E−03	1.97E−02	2.21E−03	1.16E−02	1.28E−03	4.07E−01	3.40E−02
MSSA	3.83E−01	4.72E−03	2.24E−02	5.52E−02	2.18E−03	2.67E−03	3.57E−01	5.47E−03
MOGWO	2.67E−01	3.69E−03	1.84E−02	9.68E−04	2.11E−02	1.04E−03	4.21E−01	4.61E−02
MOPSO	2.65E−01	3.68E−03	2.49E−02	1.13E−03	1.55E−02	8.90E−04	3.09E−01	3.95E−02
5000 Nodes								
MOWOA	1.53E−03	2.17E−02	1.46E−02	2.11E−03	1.89E−03	7.60E−04	3.76E−02	3.38E−02
MOGOA	1.63E−01	2.55E−03	1.87E−02	2.85E−03	1.53E−02	5.38E−03	2.17E−01	2.90E−02
MSSA	2.82E−01	3.44E−03	1.62E−01	3.82E−02	3.74E−01	6.27E−02	3.82E−01	2.82E−02
MOGWO	1.60E+00	2.21E−02	1.10E−01	5.81E−03	1.27E−01	6.23E−03	2.53E+00	2.77E−01
MOPSO	1.59E+00	3.42E−02	1.49E−01	6.76E−03	9.31E−02	5.34E−03	1.85E+00	2.37E−01

and energy consumption that nodes and sink consumed in the network through MOWOA.

In addition to the aforementioned results, the LSWSNs datasets consist of network sizes (N) from 1000 to 10,000 nodes. The algorithm is run repeatedly for $M = 10$ times for statistical results. Table 9 outlines the algorithms performance via the fitness function mentioned in Eqs. 17 and 18. This Table presents the average fitness function that obtained over M runs. The best performance is achieved by the proposed MOWOA proving its ability to choose optimal sink nodes locations effectively. Similar results are seen in Tables 10 and 11 that outlines the best and the worst fitness function obtained over M runs respectively. Also, the graphical representation are illustrated in Fig. 8.

And to aprove our proposed is best of other algorithms tested in Signal to Interference Plus Noise Ratio (SINR) Model through this equation:

$$SINR(x_i) = \frac{\frac{P(s_i)}{d(s_i, r_i)^{\alpha}}}{N + \sum_{j \neq i} \frac{P(s_j)}{d(s_j, r_i)^{\alpha}}} \geq \beta \tag{19}$$

Given a sender and a receiver pair $x_i = (s_i, r_i)$, $P(s_i)$ denotes to power level of sender s_i, $d(s_i, r_i)$ denotes to distance between sender s_i and receiver r_i and α consider path-loss exponent $\alpha \geq 1$ is a constant. The actual value of α depends on external conditions of the medium (humidity, obstacles, etc.). where N > 0 is the background noise, and where $\beta \geq 1$ is the minimum SINR required for a successful message reception.

Table 8 Results of the multi-objective algorithms on fitness function scenario for network size 6000 through 10,000

Algorithm	GD		Metric of spread		Metric of spacing		IGD	
	Ave	Std	Ave	Std	Ave	Std	Ave	Std
6000 Nodes								
MOWOA	5.10E−01	7.14E−01	4.89E−01	6.99E−01	5.23E−02	2.29E−01	1.04E−02	1.03E−02
MOGOA	5.38E−01	1.35E−03	5.97E−02	3.28E−03	3.19E−02	3.48E−03	1.67E−01	1.91E−02
MSSA	4.36E−01	2.40E−02	6.70E−01	4.25E−02	4.58E−02	5.66E−02	2.45E−01	3.48E−02
MOGWO	1.02E+00	1.43E+00	9.78E−01	1.40E+00	1.05E−01	4.58E−01	2.08E−02	2.05E−02
MOPSO	7.65E−01	1.07E+00	7.34E−01	1.05E+00	7.85E−02	3.43E−01	1.56E−02	1.54E−02
7000 Nodes								
MOWOA	5.12E−01	7.15E−01	4.64E−01	6.81E−01	6.41E−02	2.53E−01	1.28E−02	1.13E−02
MOGOA	4.30E−01	1.35E−03	5.97E−02	2.65E−03	5.34E−02	1.74E−03	1.15E−01	1.63E−02
MSSA	3.81E−01	6.47E−03	5.73E−01	3.83E−03	6.74E−01	3.17E−02	3.47E−02	5.71E−02
MOGWO	1.02E+00	1.43E+00	9.28E−01	1.36E+00	1.28E−01	5.06E−01	2.55E−02	2.27E−02
MOPSO	7.67E−01	1.07E+00	6.96E−01	1.02E+00	9.61E−02	3.80E−01	1.91E−02	1.70E−02
8000 Nodes								
MOWOA	5.17E−01	7.19E−01	5.00E−01	7.07E−01	1.05E−01	3.23E−01	2.08E−02	1.45E−02
MOGOA	5.34E−01	2.33E−03	5.98E−02	2.76E−03	3.58E−02	2.18E−03	2.13E−01	2.95E−02
MSSA	6.22E−01	3.47E−02	4.23E−02	3.82E−02	3.26E−01	3.07E−02	2.40E−02	2.36E−02
MOGWO	1.03E+00	1.44E+00	1.00E+00	1.41E+00	2.09E−01	6.47E−01	4.16E−02	2.90E−02
MOPSO	7.76E−01	1.08E+00	7.50E−01	1.06E+00	1.57E−01	4.85E−01	3.12E−02	2.18E−02
9000 Nodes								
MOWOA	5.36E−01	7.32E−01	2.21E+00	1.49E+00	3.48E+00	1.87E+00	6.92E−01	8.36E−02
MOGOA	1.60E−01	1.35E−03	6.93E−02	2.65E−03	3.80E−02	1.08E−03	3.13E−01	7.93E−02
MSSA	3.41E−01	5.26E−02	5.34E−02	3.81E−03	5.34E−02	4.67E−02	4.52E−01	4.28E−02
MOGWO	1.07E+00	1.46E+00	4.42E+00	2.97E+00	6.96E+00	3.73E+00	1.38E+00	1.67E−01
MOPSO	8.04E−01	1.10E+00	3.31E+00	2.23E+00	5.22E+00	2.80E+00	1.04E+00	1.25E−01
10,000 Nodes								
MOWOA	5.18E−01	7.19E−01	4.98E−01	7.06E−01	1.08E−01	3.28E−01	2.14E−02	1.47E−02
MOGOA	5.31E−01	3.35E−03	4.97E−02	2.75E−03	2.90E−02	2.32E−03	2.19E−01	3.94E−02
MSSA	4.37E−01	5.92E−02	5.24E−02	1.83E−02	3.66E−02	3.64E−03	3.32E−01	2.65E−02
MOGWO	1.04E+00	1.44E+00	9.97E−01	1.41E+00	2.15E−01	6.56E−01	4.28E−02	2.94E−02
MOPSO	7.77E−01	1.08E+00	7.48E−01	1.06E+00	1.61E−01	4.92E−01	3.21E−02	2.21E−02

Table 9 Mean fitness function obtained from the different algorithms

N	MOWOA	MOGOA	MSSA	MOGWO	MOPSO
1000	2.58E−02	4.49E+00	3.85E+00	6.67E−01	4.49E−02
2000	3.87E−02	4.16E+00	5.01E+00	1.00E+00	6.73E−02
3000	5.15E−02	4.25E+00	4.02E+00	1.33E+00	8.97E−02
4000	1.29E−02	3.98E+00	1.65E−01	3.34E−01	2.24E−02
5000	7.73E−02	4.55E+00	2.29E+01	2.00E+00	1.35E−01
6000	1.65E−01	3.91E+00	4.24E−01	3.31E−01	2.48E−01
7000	2.08E−01	3.84E+00	3.87E−02	4.16E−01	3.12E−01
8000	4.24E−01	3.96E+00	1.29E−02	8.48E−01	6.36E−01
9000	2.29E+01	3.87E+00	4.32E+00	4.57E+01	3.43E+01
10,000	6.14E−01	4.32E+00	5.74E+00	1.23E+00	9.20E−01
Average	2.45E+00	4.13E+00	4.65E+00	5.39E+00	3.68E+00

Table 10 Best fitness function obtained from the different algorithms

N	MOWOA	MOGOA	MSSA	MOGWO	MOPSO
1000	2.40E−02	4.82E+00	5.34E+00	2.03E+00	1.01E+00
2000	3.34E−01	5.23E+00	3.66E+01	3.04E+00	1.52E+00
3000	4.14E−01	5.09E+00	4.56E+00	4.05E+00	2.03E+00
4000	1.00E+00	5.05E+00	8.80E−01	1.01E+00	5.07E−01
5000	6.00E+00	5.38E+00	1.32E+00	3.08E+00	3.04E+00
6000	7.51E−01	5.19E+00	1.10E+00	1.50E+00	1.13E+00
7000	8.80E−01	4.96E+00	3.84E+00	1.76E+00	1.32E+00
8000	4.23E−01	6.34E−01	3.00E+00	4.56E+00	8.46E−01
9000	3.66E+01	4.53E+00	1.52E+00	5.13E+01	5.49E+01
10,000	4.34E−01	7.38E+00	5.07E−01	1.47E+00	1.10E+00
Average	4.61E+00	4.83E+00	5.87E+00	6.38E+00	6.74E+00

Table 11 Worst fitness function obtained from the different algorithms

N	MOWOA	MOGOA	MSSA	MOGWO	MOPSO
1000	3.04E−02	2.03E−02	6.08E−02	6.08E−02	2.28E−02
2000	4.73E−01	9.46E−01	7.10E−01	1.50E+00	6.31E−01
3000	2.49E−02	4.98E−02	3.74E−02	1.49E−01	3.32E−02
4000	1.52E−03	3.04E−03	2.28E−03	9.12E−03	2.03E−03
5000	6.71E−03	1.34E−02	1.01E−02	4.03E−02	1.01E−02
6000	5.48E−02	1.10E−01	8.22E−02	3.29E−01	7.31E−02
7000	1.03E+01	2.06E+01	1.55E+01	1.37E+01	1.37E+01
8000	2.43E−02	4.86E−02	3.65E−02	1.46E−01	3.65E−02
9000	1.00E−03	2.00E−03	1.50E−03	6.00E−03	1.33E−03
10,000	2.52E−01	5.04E−01	3.78E−01	1.70E+00	3.36E−01
Average	1.12E+00	2.23E+00	1.68E+00	1.77E+00	1.49E+00

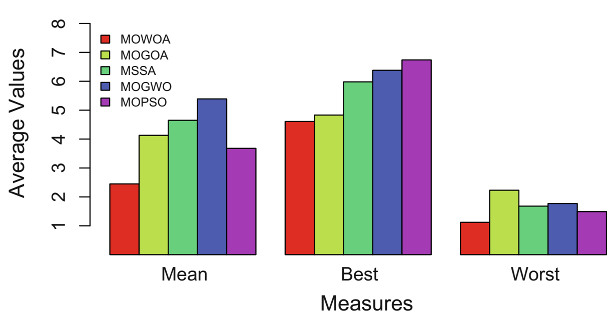


Fig. 8 Different measures for fitness function

After use Prims algorithm to find the minimum spanning tree using edge weights defined as the distance between any two nodes.

Table 12 shows the performance between MOWOA and other algorithms with $\alpha = 5$, $N = 0.01$ and $\beta = 1$ in all sized networks that tested. As seen in the table. It can also be observed that MOWOA outperforms other algorithms in most cases

In wireless sensor networks (WSN), broadcasting could allow the nodes to share their data efficiently. Due to the limited energy supply of each sensor node, it has become a crucial issue to minimize energy consumption and maximize the network lifetime in the design of broadcast protocols. The total cost of the broadcast tree is the sum of the link costs, broadcast power for all network calculated after use MST between multiple sink node and rest of nodes in network so to calculate total broadcast power for all network through sum for power of links that depicts in Table 13 which clarify proposed MOWOA outcome minimum of broadcast power cost in all sized network compared to other algorithms.

5.3 Comparison with existing studies

In this section briefly talk about comparison with the previous related studies represented in Table 14. This Table depicts the number of sensor nodes, techniques (methods have been used to choose the number of sink node) and the goal for each method. Consequently, this comparison proves that the proposed MOWOA providing the best performance in terms of minimizing the number of sink nodes and energy consumption to increase the network's lifetime

Table 12 The size of channel assignments produced by MOWOA and Other algorithms

N	MOWOA	MOGOA	MSSA	MOGWO	MOPSO
1000	166.2	203.025	238.1	287.175	295.5
2000	226.425	283.25	320.7	348.475	390.6
3000	303.075	343.85	417.35	436.3	468.15
4000	404.725	436.825	480.55	477.45	498.475
5000	454.25	497.55	834.7	872.6	936.3
6000	336.225	349.025	382.875	390.325	418.05
7000	404.025	449.4	454.975	480.775	482.5
8000	464.95	495.775	494.05	500	499.85
9000	490.7	497.55	961.1	954.9	996.95
10,000	606.15	687.7	1669.4	1745.2	1872.6

Table 13 The total broadcast power cost

N	MOWOA	MOGOA	MSSA	MOGWO	MOPSO
1000	9473.4	11,572.425	13,571.7	16,368.975	16,843.5
2000	12,906.225	16,145.25	18,279.9	19,863.075	22,264.2
3000	17,275.275	19,599.45	23,788.95	24,869.1	26,684.55
4000	23,069.325	24,899.025	27,391.35	27,214.65	28,413.075
5000	25,892.25	28,360.35	47,577.9	49,738.2	53,369.1
6000	19,164.825	19,894.425	21,823.875	22,248.525	23,828.85
7000	23,029.425	25,615.8	25,933.575	27,404.175	27,502.5
8000	26,502.15	28,259.175	28,160.85	28,500	28,491.45
9000	28,356.075	28,500	28,500	28,500	28,500
10,000	53,004.3	56,518.35	56,321.7	57,000	56,982.9

Table 14 Comparison proposed MOWOA with other studies

References	Techniques	N	Remark
[49]	PSO-based multiple-sink	300	Energy decreased
[50]	PSO with exhaustive search	300	Lifetime increased
[51]	Multiple sink location	100	Energy decreased
Proposed	MOWOA	1000:10,000	Optimal sink node location

6 Conclusions and future works

In this paper, the whale optimization algorithm (WOA) has been adapted to optimize the multiple sink node locations in large-scale wireless sensor networks (LSWSNs) and is termed as (MOWOA). To achieve that, new fitness functions are formulated to choose the minimal cardinality of sink nodes and reduce the total energy consumption. Also, there are four measures methods were used: (IGD), (GD), metric of spread and metric of spacing to evaluate the proposed MOWOA. According to experiments revealed that the proposed MOWOA can find the optimal Pareto front (PF) and find best of non-dominated solutions in comparison with four well-known optimization algorithms such as multi-objective grasshopper optimization algorithm (MOGOA), multi-objective salp swarm algorithm (MSSA), multi-objective gray wolf optimization (MOGWO), multi-objective particle swarm optimization (MOPSO). Generally speaking, according to the reported results, the proposed MOWOA has been obtained a better efficiency in reducing the total power consumption by 26% compared with the other algorithms. For future studies, MOWOA algorithm can apply to solve real-world and engineering applications such as nodes deployment and multi-hop routing between nodes and cost of sink nodes.

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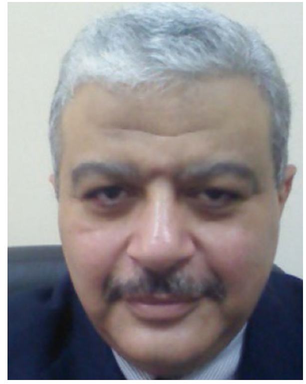
Mohammed M. Ahmed was born in Minia, Egypt in 1989. He received his B.Sc. degree in 2010 from Faculty of Computers and Information, Information System Department, Minia University, Egypt. And he received M.Sc degree from FCI-Cairo University, Information System Department, Egypt. His research interests include Data mining, Wireless Sensor Networks, Swarm Optimization, Meta-heuristics, and Machine Learning.

Essam H. Houssein received his Ph.D. degree in "Studying Some Routing Problems of Mobile Ad Hoc Networks using Artificial Ant Colony", 2012. Currently work as associate professor at CS Dept., Faculty of Computers and Information, Minia University, EGYPT. He has more than 50 scientific research papers published in prestigious international journals in the topics of machine learning and its applications. His research interests include wireless sensor networks, cloud computing, security, soft computing, Image processing, optimization, metaheuristics.

Aboul Ella Hassanien is the Founder and Head of the Egyptian Scientific Research Group (SRGE) and a Professor of Information Technology at the Faculty of Computer and Information, Cairo University. He has more than 1000 scientific research papers published in prestigious international journals and over 45 books covering such diverse topics as data mining, medical images, intelligent systems, social networks and smart environment. His other research areas include computational intelligence, medical image analysis, security, animal identification, space sciences and telemetry mining and multimedia data mining.

Ayman Taha is an assistant professor at faculty of computes and Information at Cairo University-Egypt. Ayman's research interests are GIS Systems, Spatial Data Computing, Data Mining, Machine Learning and Deep Learning. He has got the best Ph.D. thesis at Cairo University. He obtained his M.SC, and Ph.D. from the Cairo University.



Ehab Hassanien is professor at faculty of computes and Information at Cairo University- Egypt, he received Bachelor degree from Cairo University in May 1982 and Master degree in Computer Science from Northwestern University in 1989, he received Ph.D. from Northwestern University in December 1992.