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Multi-Objective Modified Flower Pollination Algorithm for Maximizing Lifetime in Wireless Sensor Networks

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Abstract: All data collected by the sensor nodes is sent to sink nodes in the Wireless Sensors Networks (WSNs). Therefore, location and the optimal number of the sink nodes has a significant impact according to the various complexity factors, it can be addressed with optimization algorithms as an optimization problem. In this study, a Multi-Objective Modified Flower Algorithm (MOMFPA) pollination has proposed to deal with the problem of multiple sink nodes in WSN in order to attain the minimum number of multiple sink nodes with reduced energy consumption to extend the lifetime of the WSN. To realize this, a fitness function has been formulated to guarantee the balance between the sink nodes and energy consumption. Moreover, to assess the performance of the proposed algorithm introduced here, it is simulated in different network sizes ranging from 100-5000 nodes and the results proved that the proposed algorithm overcomes the two well-known algorithms famous in the optimization domain such as Multi-Objective Differential Evolution (MODE) and Multi-Objective Particle Swarm Optimization (MOPSO) in terms of the number of multiple sink nodes as well as the low energy consumption. Eventually, the quantitative and qualitative results revealed that the proposed MOMFPA significantly was able to find the optimal Pareto Front (PF) and provide a superior quality of solutions.

Key words: Wireless Sensor Networks, sink node, modified flower pollination algorithm, multi-objective optimization, swarm intelligence, energy consumption, Pareto front

INTRODUCTION

Wireless Sensors Networks (WSNs) is regarded as one of the most interesting themes in information technology field and used in various fields and real-world applications. Often, WSNs consists of many sensor nodes with a limited power source that is implemented in a given area and a single data collection center which called sink node. Each node can collect information within the sensor range and then transmitted it to neighboring nodes. Sensor nodes convert significant events detected by a sink node by collaborating with other nodes. The information gathered from all nodes is ultimately sent to the base station which is called sink node (Chen and Li, 2013).

One of the most promising trends research in WSNs exploits the movement of certain components of the network (Yick *et al*., 2008). If sinks nodes are deployed statically, nearby sensors will spend much more energy than sensors away from wells. When these nodes run out of batteries, the sink nodes cannot receive other packages. Transferring the network components if sink nodes can better balance energy depletion between nodes and extend network lifetime (Basagni *et al*., 2011). Also, allocating the sink node address to the auto-configuration topology creates another problem that affects network performance in terms of power, delay and runtime. Therefore, the sink node must be accurately positioned so that the other nodes do not use extra power to provide their data and the network lifetime increases (Hacioglu and Sesli, 2016).

Consequently, one of the big challenges in WSNs is the choice of the best location of sink nodes to receive all messages from sensor nodes without consuming their energies quickly is regarded as a Multi-Objective Optimization (MOO) problem. In the multi-objective problem, there is no single optimal solution but rather a set of alternative solutions represent the optimal solutions. These solutions are optimal when there are no other solutions in the search space are superior to them when all objectives are considered; these solutions are known as Pareto Optimal (PO) solutions (Marler and Arora, 2004). This problem can be handled by combining all multiple objectives into one single objective with a set of weights. Thus, the assigning of the sink node's optimal location is a critical task to guarantee both of increasing

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network lifetime as well as energy consumption. In this study, we focus on the optimal location of the multiple sink nodes in WSNs.

Even though, the sink node location is regarded as a challenging problem in WSNs, the literature has been dealt with sink node location rarely compared to other areas like routing protocols and security, etc. in WSNs. Several studies such as Fei *et al.* (2017) presented a brief overview of the major optimization objectives utilized in WSNs and introduced some recent studies of MOO. By Mostafaei and Shojafar (2015), a novel algorithm based on an Imperialist Competitive Algorithm (ICA) has been presented to select sensor nodes. Further, four Multi-Objective (MO) metaheuristics such as Firefly Algorithm (FA), the Non-dominated Sorting Genetic Algorithm (NSGA-II), Artificial Bee Colony (ABC) and Strength Pareto Evolutionary Algorithm (SPEA2) are applied to solve the relay node placement problem in WSNs (Lanza-Gutierrez and Gomez-Pulido, 2015). Aznoli and Navimipour (2017) introduced an overview of the deployment mechanisms which have been used in WSN. In this study (Kaur and Arora, 2017), several nature inspired algorithms such as Grey Wolf Optimization (GWO), Firefly Algorithm (FA) and Flower Pollination Algorithm (FPA) are applied to estimate the optimal location of sensor nodes and the performance of these optimization algorithms are evaluated in terms of localization accuracy and number of localized nodes. By Arora and Singh (2017) butterfly optimization algorithm has employed for the node localization in WSNs. In the same context, Yang (2006) have determined the sink node location in WSNs by utilizing genetic algorithms. Chen *et al.* (2015) presented a method to select the multiple mobile sink nodes in WSNs based on Lion Optimization Algorithm (LOA) to increase the network lifetime. Moreover, the optimal location solution through utilizing the Mixed Integer Linear Programming (MILP) solution to the problem in small-scale WSNs has introduced by Hassan *et al.* (2014). By Ahmed *et al.* (2017), an algorithm based on Whale Optimization Algorithm (WOA) has proposed and the proposed fitness function is designed to reduce the numbers of active nodes and minimize energy consumption in order to prolong the network lifetime. Also, in the same context, Iqbal *et al.* (2015) addressed several optimization problems and illustrated the existing optimization solution relating to WSNs such as design, operation, deployment and placement.

Sink node localization problem is regarded as an optimization problem due to size and complexity factors. So, the optimization algorithms are quite effective to solve optimization problems, especially the multi-objective problems. Therefore, this a motivation to use nature-inspired optimization algorithms for WSN as these are robust and effective. To the best of our knowledge, little attention has been paid in utilizing other nature-inspired algorithms such as flower pollination algorithm (Ang, 2012) and the modified flowering pollination (Nabil, 2016) to solve real-world problems. A Multi-Objective localization algorithm based on the Modified Flowering Pollination called (MOMFPA) to determine the position of multiple sink nodes in WSNs was proposed in this study. As a consequence, this study differs from the literature described above in the following: each objective function is treated separately and all objective functions are evaluated for each pollen (pollen from flowers are transported by pollinators such as insects). In general, a non-dominant solution (best position) is used to guide the so-called pollen leader. At each iteration, non-dominant solutions to detect Pareto optimal solutions are stored in an external archive (Pradhan and Panda, 2012). The following key issues are addressed in MOMFPA via.; evaluating objective functions by selecting external archive leaders to promote diversity in the external archive and maintaining the external archive and the neighborhood topology used to exchange information. In addition, the greedy heuristic method (Jovanovic and Tuba, 2013) is used to generate the data transmission paths for the sensor nodes to the sink node after determining the position of the sink node. Further, the main objective of the proposed MOMFPA here is to optimally choose the position of the multiple sink nodes in the WSN in order to effectively reduce the energy consumption of the sensor nodes that are the furthest from the sink node. Eventually, the experimental results have revealed that the proposed MOMFPO significantly achieved the best location of multiple sink node as well as the low energy consumption in WSNs compared with Multi-Objective Differential Evolution (MODE) (Adeyemo and Otieno, 2009) and Multi-Objective Particle Swarm Optimization (MOPSO) (Reyes-Sierra and Coello, 2006) over different networks sizes.

Preliminaries

Modified flower pollination algorithm: Xin-She Yang proposed a new nature-inspired algorithm called Flower Pollination Algorithm (FPA) (Ang, 2012). It is inspired from the natural process 'pollination of flowers'. This metaheuristic algorithm has evolutionary characteristics and its convergence rate is relatively high as compared to other nature-inspired algorithms (Yang *et al.*, 2014). Four rules which have been derived for FPA based on the characteristics of pollination which are:

- Global pollination process is attained by considering biotic and cross-pollination because various pollinators perform levy flights
- Local pollination is attained through self- pollination and abiotic
- Flower constancy indicates the probability of reproduction which directly depends on the similarity

Switch probability p to ensure the balance between the local pollination (exploitation) and global pollination (exploration) and its value ranging by Chen and Li (2013). In overall pollination activities, local pollination can have a value of p insignificant fraction due to the various factors like physical proximity, wind, etc. These main two phases can be achieved using FPA as follows.

Global pollination process: Pollinators such as insects carry the flower pollens through long distance to guarantee that the reproduction and pollination of the fittest (g_*). Mathematically, global pollination process combined with flower constancy is formulated as follow:

$$X_i^{t+1} = X_i^t + \gamma L\left(X_i^t - g_*\right) \quad (1)$$

Where:

X_i^t = The pollen i at iteration t also the current best solution obtained is represented by g_*

γ = The step size scaling factor

L = The pollination strength which used Levy distribution (Pavlyukevich, 2007)

Local pollination process: Equation 2 demonstrates the combination of this process with flower constancy as follow:

$$X_i^{t+1} = X_i^t + \varepsilon\left(X_j^t - X_k^t\right) \quad (2)$$

To mimic the flower constancy, two pollens from the different flowers are X_k^t and X_j^t in a restricted neighborhood region of the same plant species. Also, ε is a uniform distribution by Chen and Li (2013).

On the other hand, Nabil (2016) has been proposed an extended version for the original FPA termed as a Modified Flower Pollination Algorithm (MFPA) in order to improve the local pollination through; use of the clonal property inspired by the clonal selection principle and present a step-size scaling factor γ_2 in order to modify the local pollination. This study focuses only on the MFPA as a recently nature-inspired algorithm to enhance and deal with the problem of reducing both of the numbers of multiple sink nodes and the total energy consumption in WSNs.

Multi-objective optimization: Several optimization problems are of course, multiple objectives which usually have more than one objective function that is in conflict with each other. In Multi-Objective Optimization (MOO), there are solutions but none of them can be considered as the winner. Therefore, the external archive is constructed to store a historical record obtained along the search space for the non-dominated vector. The external archive is built in the initialization phase. Then all solutions obtained are rearranged according to non-dominance compared to each other in the space to choose the non-dominant solution. Finally, any non-dominance solution is stored in the external archive.

The major aim of MOO is to locate the trade-off between conflicting objectives and the findings of MOO are a collection of solutions. Point $\vec{X}^* \in \Omega$ is a Pareto optimal if for all $\vec{X} \in \Omega$ and g = 1, 2, ..., k either, $\forall i g(f_i(\vec{X}) = f_i(\vec{X}^*))$ or there is at least one I ϵ gsuch that: $f_i(\vec{X}) \geq f_i(\vec{X}^*)$ (Coello-Coello *et al*., 2001).

Generally speaking, Multi-Objective Evolutionary optimization Problem (MOEP) (Coello *et al*., 2001) can be formulated as follow; the vector $\vec{X}^* = \left[x_1^*, x_2^*, ..., x_n^*\right]^T$ satisfies; n inequality constraints; $q_i(\vec{X}) \geq 0$ i = 1, 2,..., n the equality constraints $w_i(\vec{X}) = 0$ i = 1, 2,..., p and optimizes $\vec{f}(\vec{X}) = \left[f_1(\vec{X}), f_2(\vec{X}), ..., f_k(\vec{X})\right]^T$.

MOO problem is split into a number of single objectives and hence they are optimized concurrently. Modified Flower Pollination Algorithm (MFPA) is regarded as a new meta-heuristic was adapted to present a new version called Multi-Objective Modified Flower Pollination Algorithm (MOMFPA) to solve the multi-objective problems by using specialized fitness functions. In order to achieve that non-dominated Pareto optimal solutions are applied (Coello, 2000). As well as the multi-criterion metrics, the solutions of multi-objective problems cannot be compared using relational operators. Therefore, a non-dominant solution is a solution if and only if the following criteria are met.

Pareto dominance: V = (v_1, v_2, ..., v_n) and U = (u_1, u_2, ..., 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:

$$\begin{cases} f_i(U) \leq f_i(V) \forall i = 1, 2, ..., m \\ f_i(U) \prec f_i(V) \exists i \end{cases} \quad (3)$$

where m is the number of fitness functions (Pareto, 1964).

Pareto optimal solution: U represents the Pareto optimal solution if and only if any other solution obtained cannot be dominated by U.

Pareto Optimal Front ($PF_{Optimal}$) is a set of the Pareto optimal solutions and consists of a set of non-dominated solutions. So, the major task of the optimization algorithm is to find the most accurate approximation of true Pareto optimal solutions, i.e., convergence with uniform distributions, i.e., coverage, across all objectives (Mirjalili, 2016).

For fair comparisons among the proposed MOMFPA and the compared algorithms, in this study, to evaluate the performance of comparison algorithms four well-known assessment measures are applied. The details of each measure are explained below.

Metric of Spacing (MS): Shows the distribution of non-dominant solutions obtained by a specific algorithm (Deb, 2011) defined as follows:

$$MS = \sqrt{\frac{1}{n_{PF}-1}\sum_{i=1}^{n_{PF}}\left(d_i - \hat{d}\right)^2} \tag{4}$$

Where:

MS = The metric of spacing

d_i = The Euclidean distance between the i-th member in PF and nearest member in PF

PF = The generated Pareto front

$\hat{d}$ = The average of all distances

The Euclidean distance is defined in Eq. 5. In order to obtain the best uniform distribution in PF, a small value is assigned to S and hence, the value of S will be zero when $d_i = \hat{d}$ this means all non-dominated solutions are uniformly distributed:

$$d(a,b) = d(b,a) = \sqrt{\sum_{i=1}^{n_{PF}}\left(d_i - \hat{d}\right)^2} \tag{5}$$

Where:

a = $(f_{1a}, f_{2a}, f_{3a},...,f_{na})$

b = $(f_{1b}, f_{2b}, f_{3b},...,f_{nb})$ represents two points on the PF

Metric of spread: The spread metric (Δ) was proposed by Deb (2011) in order to set the spread achieved by non-dominated solutions which are acquired by specified algorithm. Hence, this metric can analyze how the achieved solution is extended across the Pareto Optimal Fronts ($PF_{Optimal}$) and formulated as follows:

$$\Delta = \frac{d_f + d_l + \sum_{i=1}^{n_{PF}}\left|d_i - \hat{d}\right|}{d_f + d_l + \left(n_{PF}-1\right)\hat{d}} \tag{6}$$

Where:

d_l and d_f = The Euclidean distances between the extreme solutions in $PF_{Optimal}$ and pf

d_i = The Euclidean distance between each point in PF and the closest point in $PF_{Optimal}$

n_{PF} = The total number of members in PF

$\hat{d}$ = The average of all distances

As indicated in Eq. 6, the value of Δ is always greater than zero and a small value of Δ indicates the better spread of the obtained solution; $\Delta = 0$ indicates to the best solution of $PF_{Optimal}$ having been found and $d_i = \hat{d}$ for all non-dominated points.

Generational Distance (GD): In the first, GD has been presented by Veldhuizen and Lamont (1998) to show the capability of different problems for finding a set of non-dominated solutions having the lowest distance with $PF_{Optimal}$. So, the optimization algorithm with the minimum GD results has the best convergence to $PF_{Optimal}$ (Coello and Pulido, 2005). GD measure is defined as follows:

$$GD = \frac{1}{n_{PF}}\sqrt{\sum_{i=1}^{n_{PF}} d_i^2} \tag{7}$$

Where:

n_{PF} = The number of agents in the obtained Pareto front PF

d_i = The Euclidean distance between i-th agent in PF and the nearest agent in $PF_{Optimal}$

In GD metric, the best-obtained value is equal to zero which corresponds to PF exactly covers the $PF_{Optimal}$ (Sadollah *et al*., 2015).

Inverted generational distance: The mathematical formulation of Inverted Generational Distance (IGD) similar to GD. IGD has been modified by Sierra and Coello (2005) as follows:

$$IGD = \frac{\sqrt{\sum_{i=1}^{n} d_i^2}}{n} \tag{8}$$

The true Pareto optimal solutions are indicated by n, the Euclidean distance between n and d_i which indicates the closest obtained Pareto optimal solutions. Therefore, the main difference between IGD and GD is for each true solution as far as it is the closest Pareto has been obtained in the objective space.

MATERIALS AND METHODS

The proposed MOMFPA: Pollination of flowers is a process associated with the transfer of pollen. The main actors in the implementation of this transport are insects, birds, animals, bats and other. There are flowers and insects that have done what we call pollinating flowers of association. These flowers can attract only the birds that participate in the association and these insects are regarded as the main pollinators of these flowers (Glover, 2007). A multi-objective version has been presented here in a positive way to solve a multi-objective problem called MOMFPA. And it is a population-based algorithm and therefore each pollen represents a solution in multidimensional space as the best previous experience for each pollen recorded in the external archive and must know all the main pollen solution that has been obtained (experience). Finally, when the non-dominated solutions exceeds the allocated size of the external archive, then remove the crowded members. The two main goals for the multi-objective optimization algorithm are the true Pareto optimal solutions should be obtained and the obtained solution should be well-distributed across all objectives. In addition, Algorithm 1 shows the step-by-step pseudo-code for MOMFPA in detail.

Algorithm 1 (Pseudo code for MOFPA):

```
Initialization: population Xi (i = 1, 2, ..., n), random population (pop) of
size n, identify g* which is the best solution in pop, identify p∈[0, 1] to
switch probability between global and local pollination, archive with the
obtained non-dominated solutions, iteration t = 1, maximum iteration T
While t <= T do
 For i=1 to n
   If rand >p then
  Draw vector L from levy distribution, L has D-dimension
      Apply the global pollination using eqx^{t+1}_i = x^t_i+γL (g*-x^t_i)
   Else
     Randomly choose j and k among all the solution
     Draw from uniform distribution in [0, 1]
     Do local pollination via. Eq. 2
   End if
   Calculate the objective values for each search agent
   Update the archive to the obtained non-dominated solutions
   Find the non-dominated solutions
   If the archive is full
      Add the new solution to the archive
      Run the grid mechanism to omit one of the current archive members
  End if
 End for
 X = SelectLeader (archive)
 Exclude X from the archive temporarily to avoid selecting the same leader
 Add back leader to the archive
 t = t+1
End while
Output: Return archive
```

RESULTS AND DISCUSSION

In this study, the statistical results of the proposed algorithm MOMFPA compared with MODE and MOPSO are discussed. Simulation parameters of the proposed algorithm are illustrated in Table 1. Also, the simulation nodes are supposed to mimic functions of Mica Mote sensors with energy model (Wightman and Labrador, 2011). In addition, the Network sizes (N) from 100-5000 nodes. The algorithm is run repeatedly for M = 10 times for statistical significance of the results.

Table 1: Simulation parameter

Parameters	Values
Deployment area	1000×1000 m
No. of nodes	100, 200, 400, 600, 800,1 000, 1200, 1400, 1600, 1800, 2000
Sensor node model	Mica Mote
Node sensing	range 20 m
Node communication	range 100 m
Node energy distribution	Uniform
Max energy	2000 (mA-h)
Node location distribution	Uniform

Table 2: Statistical results of sink nodes number and energy consumption obtained from the proposed algorithm MOMFPA vs. MOPSO and MODE algorithms

N	Metrics	MOMFPA	MOPSO	MODE
100	No. of sink node	4	5	4
	Energy consumption	5741	6112	6380
200	No. of sink node	4	4	5
	Energy consumption	6328	5941	6920
400	No. of sink node	4	5	6
	Energy consumption	5814	6002	7031
600	No. of sink node	5	6	5
	Energy consumption	6301	6810	7637
800	No. of sink node	6	5	7
	Energy consumption	6935	7531	8122
1000	No. of sink node	7	8	8
	Energy consumption	7112	7245	7932
2000	No. of sink node	8	9	8
	Energy consumption	7630	8351	8952
3000	No. of sink node	8	9	7
	Energy consumption	8241	8930	8623
4000	No. of sink node	10	11	10
	Energy consumption	8654	9735	9352
5000	No. of sink node	11	11	12
	Energy consumption	9130	10542	10835

Objective function: In order to adapt the MFPA to deal and handle the number of sink nodes as well as energy consumption as a multi-objective problem, two fitness functions are formulated. Equation 1 and 2 are designed as the fitness functions of the proposed algorithm:

$$F(x_1) = \sum_{i=1}^{n} \frac{N}{E_i} \tag{9}$$

$$f(x_2) = \frac{1}{\sum_{n=1}^{N_n} E_n} \tag{10}$$

Where:

- N = The No. of sensor nodes in WSN
- E_i = The energy for each sensor node
- N_n = The No. of sensor neighbor served by sink node
- E_n = The energy for each sensor node for sink's neighbours

Table 2 summarizes all obtained results for the energy consumption and sink nodes where N means the network

Table 3: Statistical results of the compared algorithms using GD, IGD, spacing and spread over network size 100 through 5000

	GD		IGD		Metric of spread		Metric of spacing	
Algorithms	Ave.	Std.	Ave.	Std.	Ave.	Std.	Ave.	Std.
100 nodes								
MOMFPA	1.70E-01	2.41E-03	0.00417756	3.75E-03	1.62E-03	2.34E-04	2.10E-04	8.45E-05
MOPSO	1.78E-01	2.46E-03	0.28056308	3.07E-02	1.23E-02	6.45E-04	1.41E-02	6.92E-04
MODE	1.77E-01	2.45E-03	0.205791727	2.63E-02	1.66E-02	7.51E-04	1.03E-02	5.93E-04
200 nodes								
MOMFPA	2.55E-01	3.61E-03	2.43E-03	3.52E-04	3.15E-04	1.27E-04	0.006266341	5.63E-03
MOPSO	2.67E-01	3.69E-03	1.84E-02	9.68E-04	2.11E-02	1.04E-03	0.420844621	4.61E-02
MODE	2.65E-01	3.68E-03	2.49E-02	1.13E-03	1.55E-02	8.90E-04	0.30868759	3.95E-02
400 nodes								
MOMFPA	3.41E-01	4.81E-03	0.008355121	7.50E-03	3.23E-03	4.69E-04	4.20E-04	1.69E-04
MOPSO	3.56E-01	4.92E-03	0.561126161	6.15E-02	2.45E-02	1.29E-03	2.82E-02	1.38E-03
MODE	3.53E-01	4.90E-03	0.411583453	5.26E-02	3.32E-02	1.50E-03	2.07E-02	1.19E-03
600 nodes								
MOMFPA	6.39E-02	9.02E-04	0.001566585	1.41E-03	6.06E-04	8.79E-05	7.87E-05	3.17E-05
MOPSO	6.67E-02	9.22E-04	0.105211155	1.15E-02	4.59E-03	2.42E-04	5.29E-03	2.60E-04
MODE	6.62E-02	9.19E-04	0.077171897	9.87E-03	6.22E-03	2.82E-04	3.88E-03	2.22E-04
800 nodes								
MOMFPA	5.07E-03	8.51E-02	0.00208878	1.88E-03	8.08E-04	1.17E-04	1.05E-04	4.22E-05
MOPSO	9.05E-02	8.89E-02	0.14028154	1.54E-02	6.13E-03	3.23E-04	7.05E-03	3.46E-04
MODE	9.96E-03	8.83E-02	0.102895863	1.32E-02	8.29E-03	3.75E-04	5.17E-03	2.97E-04
1000 nodes								
MOMFPA	1.70E-01	2.38E-01	3.47E-03	3.42E-03	1.63E-01	2.33E-01	1.74E-02	7.63E-02
MOPSO	3.40E-01	4.76E-01	6.94E-03	6.84E-03	3.26E-01	4.66E-01	3.49E-02	1.53E-01
MODE	2.55E-01	3.57E-01	5.21E-03	5.13E-03	2.45E-01	3.50E-01	2.62E-02	1.14E-01
2000 nodes								
MOMFPA	1.71E-01	2.38E-01	4.25E-03	3.78E-03	1.55E-01	2.27E-01	2.14E-02	8.44E-02
MOPSO	3.41E-01	4.77E-01	8.50E-03	7.57E-03	3.09E-01	4.54E-01	4.27E-02	1.69E-01
MODE	2.56E-01	3.58E-01	6.38E-03	5.67E-03	2.32E-01	3.41E-01	3.20E-02	1.27E-01
3000 nodes								
MOMFPA	1.72E-01	2.40E-01	6.94E-03	4.83E-03	1.67E-01	2.36E-01	3.49E-02	1.08E-01
MOPSO	3.45E-01	4.79E-01	1.39E-02	9.67E-03	3.33E-01	4.71E-01	6.98E-02	2.16E-01
MODE	2.59E-01	3.60E-01	1.04E-02	7.25E-03	2.50E-01	3.54E-01	5.23E-02	1.62E-01
4000 nodes								
MOMFPA	1.79E-01	2.44E-01	2.31E-01	2.79E-02	7.36E-01	4.95E-01	1.16E+00	6.22E-01
MOPSO	3.57E-01	4.88E-01	4.62E-01	5.57E-02	1.47E+00	9.91E-01	2.32E+00	1.24E+00
MODE	2.68E-01	3.66E-01	3.46E-01	4.18E-02	1.10E+00	7.43E-01	1.74E+00	9.33E-01
5000 nodes:								
MOMFPA	1.73E-01	2.40E-01	7.14E-03	4.90E-03	1.66E-01	2.35E-01	3.59E-02	1.09E-01
MOPSO	3.45E-01	4.80E-01	1.43E-02	9.81E-03	3.32E-01	4.71E-01	7.18E-02	2.19E-01
MODE	2.59E-01	3.60E-01	1.07E-02	7.36E-03	2.49E-01	3.53E-01	5.38E-02	1.64E-01

size. Table 2 shows the number of sink nodes obtained from the proposed algorithm less than the obtained compared with MOPSO and MODE through all networks sizes with low energy consumption.

Frequently, the proposed algorithms in the previous literature are applied medium size WSNs although, WSNs composes of hundreds or thousands of sensor nodes can be deployed, the location of multiple sinks still requires advanced studies. However, the proposed MOMFPA is applied in the different Networks sizes (N) according to the fitness function. To test the cardinality of sink nodes of the proposed algorithm, 30 iterations were tested on the same network. After all, the results are presented in Table 3 and Fig. 1.

Table 3 shows the statistical results using GD, IGD, spread and spacing obtained by the proposed and the compared algorithms. Table 3 revealed that the MOMFPA outperforms the MOPSO and MODE on most of all networks sizes. In order to evaluate the superior convergence of the proposed algorithm introduced here can be deduced from the obtained results of GD and IGD. According to the results collected by the GD revealed that the MOMFPA surpasses the MOPSO and MODE.

Figure 1 displays the PF obtained by MOMFPA with the fitness function for all network size. As noticed from Fig. 1, the MOMFPA provides superior results toward most of the true Pareto-optimal fronts and competitive convergence compared with the MODE and MOPSO algorithms.

As a summary, it's clear from the aforementioned results, the proposed MOMFPA has been achieved better results in terms of energy consumption and an optimal number of sink nodes on the majority of the networks sizes employed. Due to the fact of minimal transmission cost from the source nodes to the sinks for MOMFPA. Also, the balance between a number of sink nodes and

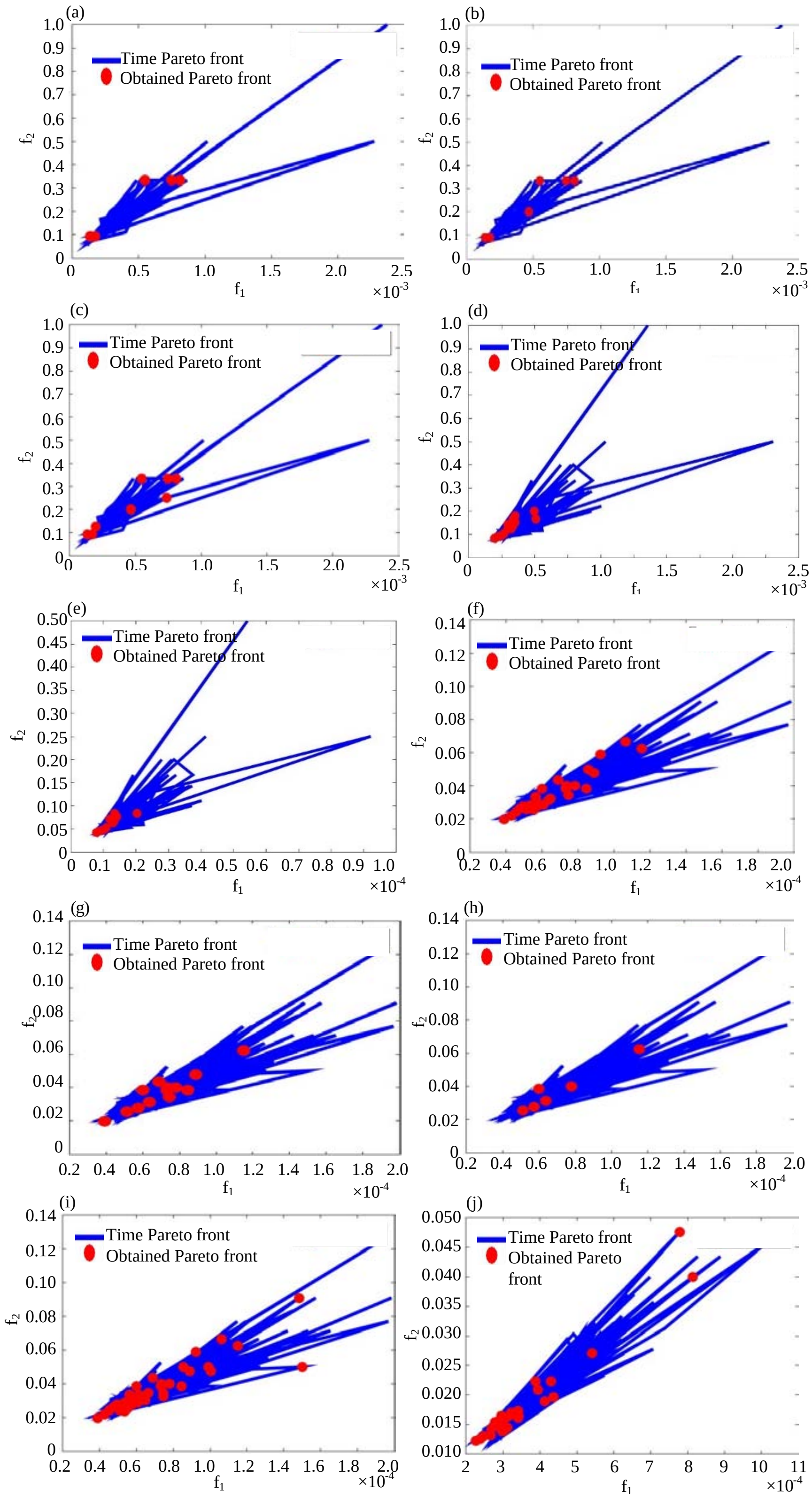

Fig. 1: Best Pareto optimal front obtained by MOMFPA over networks sizes 100 through 5000: a) 100; b) 200 ; c) 400; d) 600; e) 800; f) 1000; g) 2000; h) 3000; i) 4000 and j) 5000 nodes

Table 4: Mean, worst and average fitness function obtained from the different algorithms

Nodes	Metrics	Mean	Best	Worst
100	MOMFPA	8.59E-03	6.67E-01	1.01E-02
	MOPSO	2.22E-01	6.75E-01	1.81E-01
	MODE	1.50E-02	3.38E-01	1.99E-02
200	MOMFPA	1.29E-02	1.00E+00	1.52E-02
	MOPSO	3.34E-01	1.01E+00	2.72E-01
	MODE	2.24E-02	5.07E-01	2.99E-02
400	MOMFPA	1.72E-02	1.33E+00	2.03E-02
	MOPSO	4.45E-01	1.35E+00	3.62E-01
	MODE	2.99E-02	6.75E-01	3.98E-02
600	MOMFPA	3.22E-03	2.50E-01	3.80E-03
	MOPSO	8.34E-02	2.53E-01	6.79E-02
	MODE	5.61E-03	1.27E-01	7.47E-03
800	MOMFPA	4.30E-03	3.33E-01	5.07E-03
	MOPSO	1.11E-01	3.38E-01	9.05E-02
	MODE	7.48E-03	1.69E-01	9.96E-03
1000	MOMFPA	5.51E-02	2.50E-01	3.16E-01
	MOPSO	1.10E-01	5.00E-01	6.32E-01
	MODE	8.27E-02	3.75E-01	4.74E-01
2000	MOMFPA	6.93E-02	2.93E-01	4.14E-01
	MOPSO	1.39E-01	5.87E-01	8.28E-01
	MODE	1.04E-01	4.40E-01	6.21E-01
3000	MOMFPA	1.41E-01	1.41E-01	2.85E-01
	MOPSO	2.83E-01	2.82E-01	5.70E-01
	MODE	2.12E-01	2.11E-01	4.28E-01
4000	MOMFPA	7.62E+00	1.22E+01	1.36E+01
	MOPSO	1.52E+01	2.44E+01	2.72E+01
	MODE	1.14E+01	1.83E+01	2.04E+01
5000	MOMFPA	2.05E-01	2.45E-01	2.50E-01
	MOPSO	4.09E-01	4.90E-01	5.01E-01
	MODE	3.07E-01	3.67E-01	3.75E-01

Table 5: Comparison proposed MOMFPA with other studies

Ref.	Techniques	Nodes	Remarks
Yang (2006)	Flower pollination algorithm	100	Minimizing the localization error
Chen *et al.* (2015)	Butterfly optimization algorithm	25-150	Consistent location of nodes
Iqbal *et al.* (2015)	Lion optimization algorithm	100	Lifetime increased
Srinivasa *et al.* (2016)	PSO-based multiple-sink	300	Energy decreased
Dandekar and Deshmukh (2013)	PSO with exhaustive search	300	Lifetime increased
Kaur *et al.* (2016)	Multiple sink location	100	Energy decreased
Proposed	MOMFPA	1000: 5000	Optimal sink node location

energy consumption that nodes and sink consumed in the network. In addition to the aforementioned results, Table 4 outlines the performance of the algorithms using the fitness function. Table 4 shows the average fitness, best and worst values obtained over M runs. The best performance is achieved by the proposed MOMFPA proving its ability to choose optimal sink nodes locations effectively.

Comparison with existing studies: However, a brief comparison with the previous related studies is depicted in Table 5. The information about the proposed techniques (methods have been used to choose the number of sink node) and Network size (N) reported in previous studies are recorded. Consequently, it is clear that the proposed MOMFPA providing the best performance in comparison with the recent algorithms described in Table 5, in terms of minimizing the number of sink nodes and energy consumption in order to increase the network lifetime. Another advantage of the proposed algorithm is MOMFPA tackle with the sink nod localization as a multi-objective problem.

CONCLUSION

A modified flower pollination algorithm has been adapted to optimize the multiple sink node which is regarded as a Multi-Objective problem in WSNs and is termed as (MOMFPA). In addition, a newly designed fitness function is applied in order to select the minimal number of sink nodes and reduce the total energy consumption. To evaluate the proposed MOMFPA, ten different network sizes and four assessment metric has been applied. The statistical results indicated that the MOMFPA has been achieved better efficiency on reducing a total number of sink nodes and the power consumption. In addition, the simulation results confirmed that the proposed MOMFPA was able to find the optimal

Pareto Front (PF) in comparison with well-recognized algorithms in the optimization domain like Multi-Objective Differential Evolution (MODE) and Multi-Objective Particle Swarm Optimization (MOPSO).

RECOMMENDATIONS

For future work, we will try to employ the MOMFPA algorithm in different applications such as multi-hop routing and the cost of sink nodes. Moreover, different modifications will be added to the MOMFPA such as using chaotic maps. Generally speaking, the research on multiple sink nodes in WSNs is more complicated and needs further investigation.

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