SALP Swarm Optimization Approach for Maximization The Lifetime of Wireless Sensor Network

Mohammed M. Ahmed

*Abstract***:** *In recent years, the maximization of a lifetime for wireless sensor networks is considered an important area for researchers. The wireless sensor networks (WSNs) contain two types of sensors that called sensor nodes and sink nodes which sensor node send information to the central node (sink node) that collected its data. Choosing the best location of sink node considered the critical problem that faces the lifetime of wireless sensor networks. In this paper, we propose a method that choosing best location of a sink node by applying Salp Swarm Algorithm (SSA) after determining sink node location we create transmission paths between the sink node and rest of nodes using Prim's minimum spanning tree to choose shortest paths. Accordingly, for fitness function that used to decrease energy consumption for a network. Simulation results clarify that our proposed algorithm that solves localization of sink node presents the best results for prolonging the network's lifetime compared to Cat Swarm Optimization algorithm (CSA) and Particle Swarm Optimization (PSO).*

*Keywords***:** *Wireless sensor networks (WSNs), sink node placement, Salp swarm algorithm (SSA)..*

I. INTRODUCTION

Nowadays, Wireless sensor networks (WSNs) are used in many of fields such as security surveillance, health, military, habitat monitoring, disaster management, and WSN have a large number of sensor nodes that monitor specific region and sink node which collect data that receive from sensor node in network [1]. The most important applications for WSNs is monitoring earthquake remotely before earthquake waves occurred in specific region [2] by choosing the best location of the central seismic station.

Many researchers are interested in single sink node localization to improve the network's lifetime. In [3] proposed the 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. In regards of the node localization, the determination of sink node location in a small WSNs based on cat swarm optimization algorithm (CSA) was proposed in [4] and compared with particle swarm

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optimization (PSO) in [5]. In [6] 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.

In [7] proposed the method by Yadav et al. that solve the clustering problem via PSO with using a distance of transmission for sensor nodes and residual energy. The best methodologies that saving energy for wireless sensor networks called topology control protocol (TC) such as the coverage and network's connectivity [8], [9] but Security is considered one of the problems that face TC [10].

Although the location of the sink node is one of the most important problems facing WSNs, many researches such as [10] presented a method for choose best of multiple sink nodes in LSWSNs. In most of the papers, the sensor node that deployed uniformly in a geometric region such ad rectangular area or circular area, the location of sink node will be located in the middle of the area such as in [11] that proposed P-Median Problem model. The Even though the sink node location is an obvious problem in WSNs, the literature has been dealt with sink node location rarely compared to other areas. Although the location of the sink node is one of the most important problems facing WSNs, many researchers such as [12] presented a method for choose best of multiple sink nodes in LSWSNs that choose best of multiple sink nodes locations. Also, in [13] proposed to allocate multiple sink nodes location in WSN and transmission path from all sensors to these multiple sink nodes.

This paper presents a new method that solves the localization of sink node in WSNs based on salp swarm algorithm (SSA) [14] called (SSA). This work proposes to solve the problem of choosing the best location single sink node Followed by a decrease in energy consumption and prolong the network's lifetime in WSNs. thereafter, uses the method of the greedy algorithm [15] such as Prim's algorithm [16] to create transmission paths from sink node to all rest of nodes in the network that regards a minimum spanning tree (MST) [17] algorithm which chooses shortest paths. Finally, the results of SSA is compared with other swarm optimization algorithms such as Cat Swarm Optimization algorithm (CSA) and Particle Swarm Optimization (PSO). In this paper introduces an effective method by combining the multi-objective technique with the bird swarm algorithm (BSA) to obtain a new method called MBSA[22].

And we can then develop the proposed algorithm SSA-based sink node placement to become multi-objective algorithm to overcome many of the objectives that represent Pareto optimal

(PO) solutions [18] [19].

The structure of this paper is organized as follows. Section 2 presents an overview related to our methodologies. Section 3 introduces the proposed SSA-based sink node placement. The performance evaluation of the proposed algorithm with the existing algorithms is presented in Section 4. Conclusion are presented in Section 5.

II. PRELIMINARIES

A. Network Model

In this paper, WSNs have a set of sensor nodes and have one single sink node. All sensor nodes distributed randomly in an area called R that defined $R = L * L$, where L represents the side length. this network is deployment by attaraya simulator that extracts a deployment network with coverage and connectivity. there are some of the assumptions for a network that follows: Firstly, assume there are set of sensor nodes that defined by $N = \{n1, . . ., nk\}$. Secondly, all sensor nodes have different energy and the same communication range and same sensing range. Finally, there is a single sink node in the network that is located in a different location that chooses the best location for the sink node in this paper.

B. Topology Control

The Topology control (TC) [20] contains two types that called Topology Construction and Topology Maintenance. The first type Topology Construction is to construct miniature topology network of a smaller number of active nodes and minimizing transmission power. The second type Topology Maintenance aims to repair the constructed topology network with the collaboration of formerly inactive nodes. This maintenance procedure allows all nodes to participate within the network.

The target of TC protocols is maximizing the network's lifetime with the balance between energy consumption and radio interferences reductions. However, TC protocols have some drawbacks such as security for TC protocols Which affect negatively on the efficiency of the network such as protocols [10]. Most of the TC protocols that explained in researches such as A3 [8] and A3Cov [21] assume the sink node location is in the center of the network if the deployment of the network is uniformly so this case is not best result in normal life. So, in this paper proposes a contribution to extending the network's lifetime using salp swarm algorithm (SSA) based sink node placement to find the best location of sink node in the network.

C. Salp Swarm Algorithm

All Salp Swarm Algorithm (SSA) was proposed by Mirjalili et al. [14], and mathematically has been modeled as follows:

The leader position updated by the equation:

$$X_k^1 = \begin{cases} F_k + c_1\left((ub_k - lb_k)\right)c_2 - lb_k & if\ c_3 \geq 0 \\ F_k + c_1\left((ub_k - lb_k)\right)c_2 - lb_k & if\ c_3 < 0 \end{cases} \quad (1)$$

Where X_k^1 represents the position of the first leader salp during kth dimension, F_k represents position source of food in the kth dimension, the upper bound of kth dimension represented by ub_j, the lower bound of kth dimension represented by lb_j, and c_1, c_2, and c_3 calculated by random numbers.

The coefficient c_1 is the most important parameter in SSA because it balances exploration and exploitation defined as follows:

$$c_1 = 2e^{-\left(\frac{4l}{\pi}\right)^2} \quad (2)$$

The current iteration represented by l and the maximum iteration represented by L.

The position of the followers updated by an equation:

$$x_k^i = \frac{1}{2} at^2 + v0t \quad (3)$$

Where $i \geq 2$, x_j^i shows the position of i th follower salp in k th dimension, t is time, v0 is the initial speed, and $a = v_{final}/v_0$ where $v = x-x_0/t$.

$$x_k^i = \frac{1}{2}\left(x_k^i + x_k^{i-1}\right) \quad (4)$$

Where $i \geq 2$ and the position of i th follower salp in kth dimension represented by x_k^i. With Eq.1 and Eq.4.

III. THE PROPOSED SINK NODE PLACEMENT USING SALP SWARM ALGORITHM

This section describes the design of salp swarm algorithm for sink node placement (SSA-based sink node placement) as shown in Fig 1 and the detailed pseudo code of the SSA-based Sink node placement is illustrated in Algorithm 1.

Although most of the researches suppose that the location of the sink node in the center of the network such as A3, A3Cov topology control Protocols. this is not an optimal situation in real experiments. So better to improve the selection sink node location to save the network's coverage and operational lifetime

To select the location of the sink node in WSNs, the residual energy equipped on the sensor nodes are assumed to be randomly distributed network in this paper for finding the best location of the sink node. In our proposed SSA-based sink node placement, every salp represents a potential location of the sink node, and the salp with the best fitness value is capable to determine the final location of the sink node in the WSNs.

The steps for achieving the goal with SSA is listed as follows in Fig 1. This paper introduces a solution to the optimization problem, where the fitness function is minimizing optimal sink node located in a WSNs and reducing energy consumption.
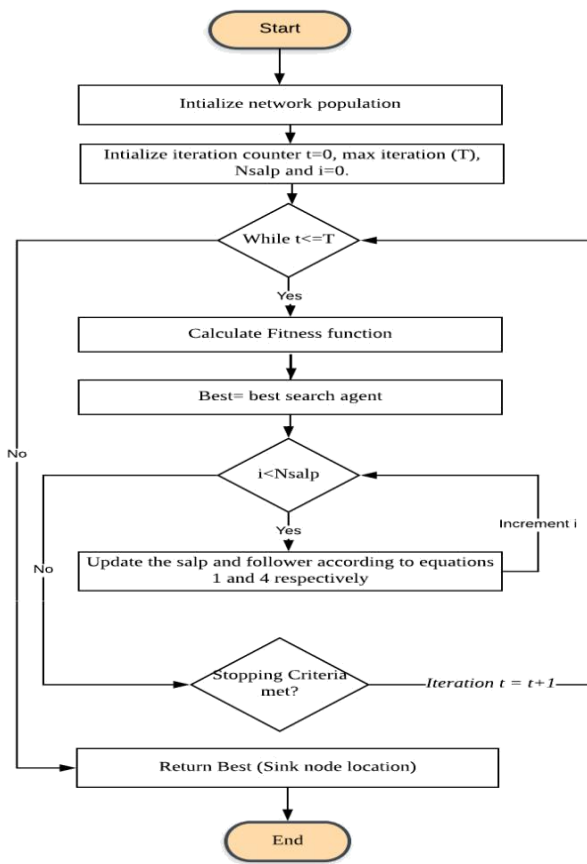
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Figure 1: The architecture of the SSA-based sink node placement.

Algorithm 1 The proposed SSA-based sink node placement algorithm.

1: Input: A graph represents the nodes with energies
2: Output: Best location of sink node
3: Initialize the salp population x_i; (i = 1, 2, …,n).
4: Initialize ub, lb.
5: Initializing start of iteration t = 1 and initialize Maximum of iteration T.
6: while t <= T do
7: Calculate the fitness function for each search agent (sink node) by Eq5.
8:   Best= the best search agent.
9:   Update c_1b Eq.
10: for all search agents of x_i
11: if i == 1 then
12: Update sink node by Eq.1
13: Else (|A| ≥1)
14: Update follower of sink node by Eq.4
15: end if
16: EndFor
17: Amend the salps based on the upper and lower bounds of variables
18: end while
19: Return Best (Sink Node Location).

IV. FITNESS FUNCTION

The performance of SSA evaluated via the location of the sink node and energy consumption in different algorithms such as CSA and PSO. Equation 5 is considered the fitness function of the proposed algorithm.

$$f(x) = \propto_1 \frac{AN}{N} + \propto_2 \sum_{i=1}^{N_{neighbor}} E_{neighbor} + \propto_2 TDis \quad (5)$$

Where AN represents the number of active nodes, $N_{neighbor}$ represents set of neighbors that served by sink node, and $E_{neighbor}$ represents energy for each sensor node that is considered neighbor for the sink node that selected and TDis is the total distances between the sink node and all sensor nodes and in Table 1 clarifies parameter setting.

V. EXPERIMENTAL RESULTS AND DISCUSSION

In this section discusses the experiment results for the proposed algorithm SSA compared to CSA and PSO. In Table 1 illustrates simulation parameters Which have been used in all experiments.

All the results are executed using the same PC that has settings which clarify in Table 2.

Table 1. Atarraya simulation parameter.

Parameter	Value
Deployment area	600m * 600m
Number of nodes	100,200,...,1000
Sensor node model	Simple
Node communication	range 100m
Node sensing	range 20m
Node location distribution	Uniform
Node energy distribution	Uniform
Max energy	1000 milliamperes-hour(mA-h)
$\propto_1$	0.3
$\propto_2$	0.1
$\propto_3$	0.5

Table 2. 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

The target from this experiment is to verify the proposed SSA algorithm and compare it with two algorithms CSA and PSO. In this experiment, in Table 3 depicts the running time of the proposed algorithm SSA is better than another algorithms CSA and PSO.

Table 3. Running Time for the different algorithms per second.

N	SSA (s)	CSA (s)	PSO (s)
100	196.9	396.9	395.3
200	735.8	1135.8	1303.6
300	1473.1	2073.1	2509.6
400	3648.0	4448.0	5872.1
500	5058.5	6058.5	8087.7
600	6825.4	8025.4	10838.0
700	9674.7	11074.7	15212.0
800	11356.3	12956.3	17834.4
900	14247.4	16047.4	22271.1
10000	17450.0	19450.0	27174.9

A. Results and discussion

Define All obtained results summarize energy consumption for compared algorithms SSA, CSA and PSO in Table 4. This table clarify proposed sink node placement using salp swarm algorithm overcome on other algorithms.

Table 4. Energy Consumption for the different algorithms.

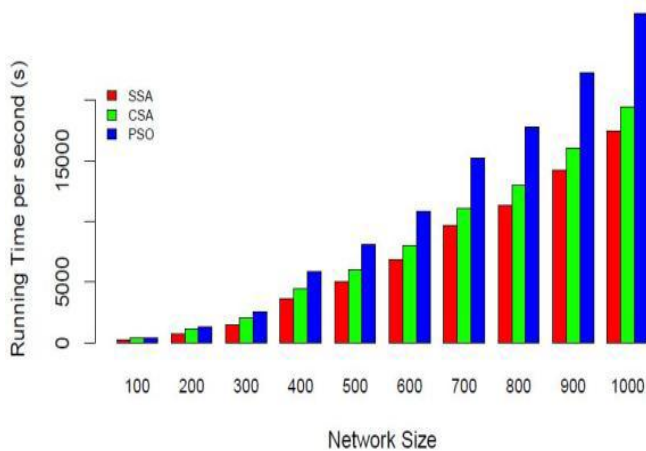| N	SSA (s)	CSA (s)	PSO (s)
100	9102	10354	12855
200	8932	11729	11847
300	10296	13520	12843
400	9347	11254	11935
500	10352	13956	12739
600	11732	14258	13654
700	10368	13547	15326
800	12635	13952	15466
900	12864	14963	13756
10000	11285	16302	15356

Fig. 2: Running Time for algorithms SSA, CSA and PSO for all network sizes.
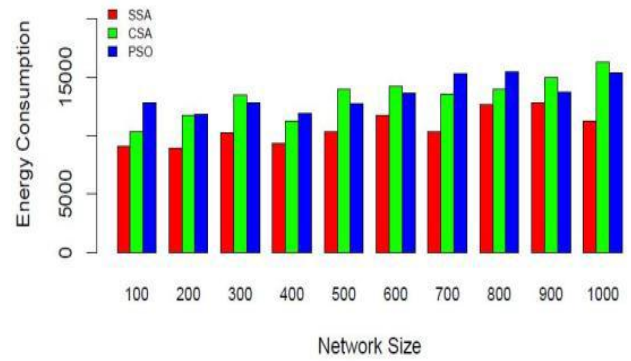

Fig. 3: Energy Consumption for algorithms SSA, CSA and PSO for all network sizes.

Fig 4 and 5 depicts position of sink node for 100 and 200 nodes respectively and clarify transmission path from each sink node that selected by each algorithm and the rest of sensor nodes in the network via minimum spanning tree [15] such as Prim's algorithm [16] that used with proposed SSA-based sink node placement that solves sink node placement. Note the results that appear with the proposed SSA when the number of nodes increased in the network give better results compared with the other algorithms CSA and PSO in terms of sink location and energy consumption.
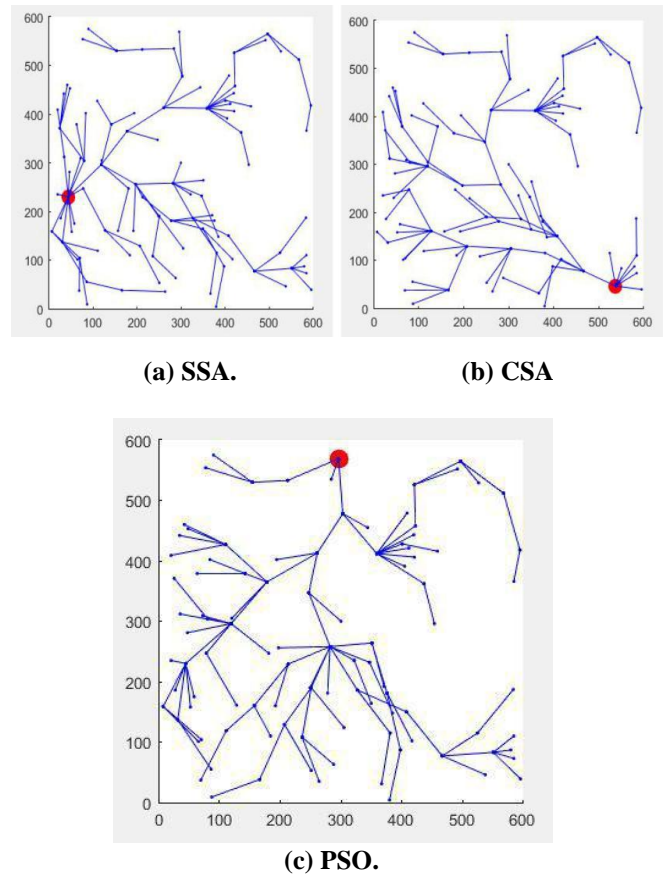

(a) SSA.   **(b) CSA**

(c) PSO.

Fig. 4: Location of sink node in network size 100 for SSA, CSA and PSO.

VI. CONCLUSION

In this paper, the salp swarm algorithm (SSA) has been adapted to optimize the single sink node location wireless sensor networks (WSNs) with using Prim's minimum spanning tree to choose shortest paths that called to data transmission paths from the sink node to the rest of nodes in network Accordingly we propose a fitness function that use to reduce energy consumption for the network. According to the experiments that our proposed strategy executed for 10 different network size, the results prove that our method is better results for decreasing energy consumption compared with the other algorithms Cat Swarm Optimization algorithm (CSA) and Particle Swarm Optimization (PSO). To extend this contribution for future work for this direction of sink node placement. SSA can be adapted to improve using the multi-objective concept to overcome more than one objective for this direction of WSNs such as reducing energy and coverage and more of objectives.
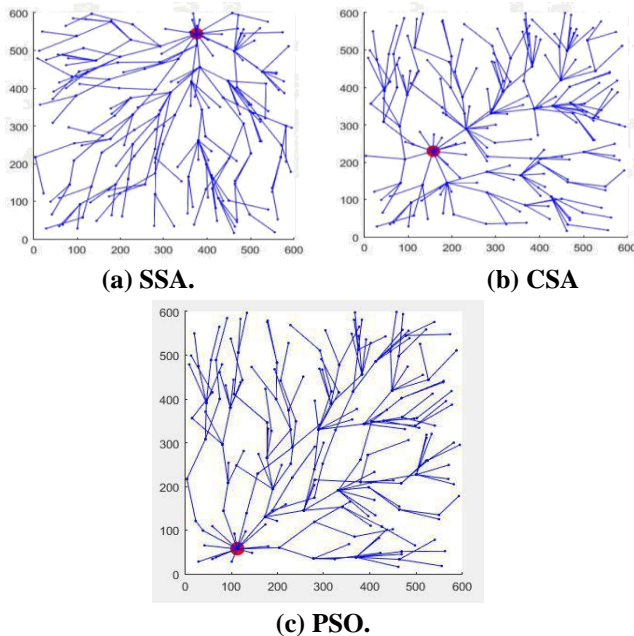

(a) SSA.   **(b) CSA**

(c) PSO.

Fig. 5: Location of sink node in network size 200 for SSA, CSA and PSO.

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