Comparative study between metaheuristic algorithms for internet of things wireless nodes localization

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ABSTRACT

Wireless networks are currently used in a wide range of healthcare, military, or environmental applications. Wireless networks contain many nodes and sensors that have many limitations, including limited power, limited processing, and narrow range. Therefore, determining the coordinates of the location of a node of the unknown location at a low cost and a limited treatment is one of the most important challenges facing this field. There are many meta-heuristic algorithms that help in identifying unknown nodes for some known nodes. In this manuscript, hybrid metaheuristic optimization algorithms such as grey wolf optimization and salp swarm algorithm are used to solve localization problem of internet of things (IoT) sensors. Several experiments are conducted on every meta-heuristic optimization algorithm to compare them with the proposed method. The proposed algorithm achieved high accuracy with low error rate (0.001) and low power consumption.

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1. INTRODUCTION

The internet of things (IoT) depends on powerful technologies such as wireless sensor networks (WSN) and Radio-frequency identification (RFID), which have changed the current world in which we live in conjunction with the tremendous development in sensor technology and cloud computing [1]-[3]. This development led to some problems in identifying remote sensing areas and linking them together. There are also other challenges, such as providing a safe environment for this type of wireless network, and there is another challenge in how to create a coordinated and synchronous link between different sensing means that perform the same task. You can learn how to create an ontology to link data and important points that perform the same task through research [4], [5].

WSNs are small network nodes that record their surroundings collectively. WSNs are used in several applications, such as weather, location search, location, hygiene, home self-regulation, and transportation control. The sensor system contains a sensor segment, a conversion segment, and a power sector. There are various types of sensor nodes. The primary type is the Prospector, which handles as Calculator. The second type is thermal prospectors. The final third type is some of the things that are related to feelings [6], [7].

Localization is a significant problem in WSN. The positioning of a particular node position is defined as a localization dilemma. In WSN, there will be many unlocalized nodes, densely packed in places that may not be identified. In addition, the large number of devices in the IoT leads to problems with power consumption. In addition, the internet of things system is complex and dynamic. Therefore, many algorithms of the international system have been developed to account for such complex activities involving simple people.

The global positioning system (GPS) can be used to locate the sensor nodes. The base station is listening to GPS to find the coordinates of the sensor. But this method is expensive. An alternative approach is communicating and listening beacon nodes [6]. In general, localization algorithms that are not affected by GPS changes can be used in band-dependent and band-free authorizations. In distance-dependent localization algorithms, a point-to-point distance setting or an angular line between sensor nodes is used. Under these circumstances, the sensor nodes' settings are given with the help of a triple anchor. In contrast to area switch location algorithms, domain-free location algorithms do not remove any information required to belong to unknown nodes.

In the previous related works, combinations of metaheuristic methods have been utilized to resolve the localization dilemma in WSNs. Various optimization algorithms in wireless sensor networks (WSN) such as practical swarm optimization (PSO), salp swarm algorithm (SSA), butterfly optimization algorithm (BOA), grey wolf optimization (GWO), bacterial foraging algorithm (BFA), artificial bee colony algorithm (ABC), H-best particle swarm optimization (HPSO), biogeography-based optimization (BBO), genetic algorithm (GA), and the artificial bee colony (ABC) are used to solve the localization problem. The document's main contribution is to conduct several experiments using hybrid meta-heuristic optimization algorithms to solve the localization problem in WSNs. Results were analyzed using many meta-heuristic algorithms according to performance, speed, and cost. These contributions will be summarized as follows: i) use hybrid meta-heuristic optimization algorithms to solve the localization problem. ii) solve power limitation in IoT sensors by enhancing meta-heuristic optimization algorithm, iii) conduct several experiments to prove the efficiency of the system used, iv) make a comparison between related works and proposed method. Table 1 represent some of the related works.

The remaining parts of this manuscript are designed as follows: section 2 provides a brief explanation of the various meta-heuristic algorithms. Section 3 introduces the research method and the proposed algorithm to solve the localization problem using a hybrid of meta-heuristic algorithms. Section 4 covers the implementation of experiments and the discussion of the results. Finally, Section 5 represent the conclusion.

Table 1. Literature review of some related works

Ref.	Year	Metaheuristic algorithm	Localization technique	Mean localize error
[8]	2009	PSO and BFA	Anchor based-Range based	PSO: 0.3 BFA: 0.2
[9]	2011	PSO and ABC	Anchor based-Range based	PSO: 25.3 ABC: 34.1
[10]	2011	DV distance and PSO	Anchor based-Range based	SAL: 21% TSA: 14%
[11]	2012	PSO and HSPO	Anchor based-Range based	PSO: 0.184 HPSO: 0.138
[12]	2012	PSO	Mobile Anchor Broadcasts	Too many Results
[13]	2012	Genetic and ANN	Anchor based-Range based	RMSE is 0.41 meters
[14]	2012	Adaptive PSO	Anchor based-Range based	PSO DV-HOP: 0.38
[15]	2013	BBO and PSO	Anchor based-Range based	PSO: 0.33 BBO: 0.52
[16]	2014	PSO and Binary PSO	Anchor based-Range based	PSO: 0.109 BPSO: 0.122
[17]	2014	DV-hop based on Genetic Algorithm	Anchor based-Range based	DV-HOP: 8.8% GADV: 6.5%
[18]	2015	PSO, Genetic and Firefly Algorithm (FA)	Anchor based-Range based	PSO: 0.1 GA: 0.4 FA: 0.8
[19]	2017	BOA and PSO	Anchor based-Range based	BOA: 0.21 PSO: 0.78
[20]	2017	PSO and GWO	Anchor based-Range based	PSO: 0.30 GWO: 0.658
[21]	2019	PSO and ABC	Anchor based-Range based	Too many results

2. METAHEURISTIC ALGORITHMS

This article will create a new algorithm that addresses the localization problem of different sensors in the wireless sensor network using anchors nodes by combining several algorithms, namely PSO, GWO, and SSA. Therefore, the pseudocodes for each algorithm are described in this section [22].

2.1. Practical swarm optimization (PSO)

PSO is a computational approach that enhances a research problem by repeatedly attempting at a given scale of quality to develop a candidate's solution concerning. It solves a difficulty by having a set of particles and moving these particles in the search space according to easy mathematical equations on particle position and velocity. Each particle's motion is influenced by its most prominent local location but is also directed towards the best-known places in the search space, which are updated as other particles found more suitable positions. The ith particle in the swarm can be denoted as $p_i = [p_{i1}, p_{i2}, \dots, p_{id}]$ and its speed can be denoted by vector $S_i = [s_{i1}, s_{i2}, \dots, s_{id}]$. Let the best location ever visited in the past by the ith particle be denoted by $L_i = [L_{i1}, L_{i2}, \dots, L_{id}]$. After many times, the whole swarm is partitioned into more miniature sub-swarm, and each sub-swarm has its own local best particle. Algorithm 1 introduces the pseudo code of PSO.

Algorithm 1. Pseudocode of PSO
```
Function Start
   Generate initial population of m particles
   While (t  <Max_Gerneration)
        Foreach m
              measure fitness value
              best_fitness = fBest
              Current value = new_fBest
        End Foreach_loop
        Select m with fBest
       Assign value = gBest
       For each particle
             Measure velocity
             Set Position
       End For_loop
   End While_Loop
```

2.2. Butterfly optimization algorithm (BOA)

Arora and Anand [23] produced a metaheuristic algorithm based on a mathematical model, inspired by nature, to find food for butterflies, and this is a good strategy for research, which is BOA. Butterflies use sensory receptors to determine the source of their food/nectar. These sensory receptors, also called chemoreceptors, can perceive smells and are scattered throughout a butterfly's body. Algorithm 2 introduces the pseudo-code for BOA.

Algorithm 2. Pseudocode of BOA
```
Function Start
PoB = population of Butterflies
Set t := 0 (counter initialization)
While t  <maximum counter do
      Foreach x in PoB do
            measure fitness function for x
      End Foreach
      Find best x
     Foreach x in PoB do
        n = random value from [0,1]
         If n < t then
                 g = best solution
               Move towards g
         else
               Move randomly
         End If
         Evaluate the fitness function
         Assign and Update g
  End Foreach
End While
Return g
End Function
```

2.3. Grey wolf optimization (GWO)

Mirjalili *et al.* [24] was developed a new algorithm also inspired by nature, but this algorithm focuses on gray wolves' social behavior and this method is called GWO. The GWO method assumes the management authority and hunting mechanism of gray wolves in nature. Four gray wolves, such as alpha, beta, delta, and omega are adopted to assume leadership authority. Gray wolves remain in combinations of 5-12 wolves. α, and are four gray wolf classes that follow a rigid common hierarchy. α is the authoritative wolf between wolves who perform various decisions, attended by other yielding gray wolves. During the hunting manner, the wolves can invest their victim in a way that can be mathematically represented as (1), (2):

$$\vec{D} = \left|\vec{C}.\vec{X_p} - \overrightarrow{X_{(L)}}\right| \quad (1)$$

$$\overrightarrow{X_{(L+1)}} = \left|\overrightarrow{X_{p(L)}} - \vec{A}.\vec{D}\right| \quad (2)$$

The vectors coefficient named A⃗ and C⃗ can be demonstrated as (3), (4):

$$\vec{A} = \left|\overrightarrow{rand1}.2\vec{a} - \vec{a}\right| \quad (3)$$

$$\vec{C} = 2\,\overrightarrow{rand2} \quad (4)$$

2.4. Salp swarm algorithm (SSA)

Mirjalili *et al.* [25] proposed an algorithm inspired by the natural marine environment, called salp, to solve the improvement problems with single or multiple goals. This work presents a new optimization algorithm called the salp swarm algorithm (SSA) and the salp swarm multipurpose algorithm (MSSA), which breeds crowds when navigating and foraging in the ocean. These two algorithms are examined on numerous numerical optimization functions to control and confirm their effective operations in determining optimal solutions to optimization difficulties. Figure 1 represents the SSA flowchart.

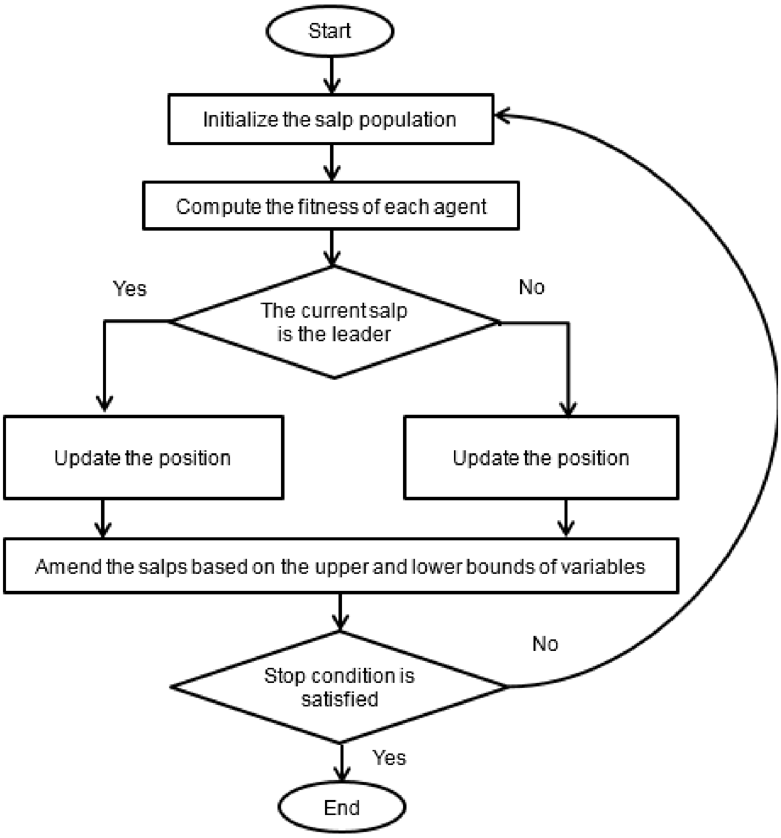


Figure 1. Flow chart of SSA

The mathematical function results show that the SSA algorithm can efficiently optimize the first random solutions and concentrate on the better. To find out the leader's position, we suggest (5), and it can also determine and update the leader's position [25]:

$$x_j^1 = \begin{cases} F_j + c_1\left((ub_j - lb_j)c_2 + lb_j\right) & c_3 \geq 0 \\ F_j - c_1\left((ub_j - lb_j)c_2 + lb_j\right) & c_3 < 0 \end{cases} \quad (5)$$

where x_j^1 shows the position of the first salp (leader) and c_1, c_2, and c_3 are random numbers. As shown in (5) shows that the leader only updates its position with respect to the food source.

$$c_1 = 2e^{-\left(\frac{4l}{L}\right)^2} \tag{6}$$

Where L = max of iterations.

$$x_j^i = \frac{1}{2} a\, t^2 + v_0 t \tag{7}$$

Considering $v_0 = 0$, this equation can be expressed as (8):

$$x_j^i = \frac{1}{2} \left(x_j^i + x_j^{i-1}\right) \tag{8}$$

3. PROPOSED METHOD

Our method's principal objective is locating target IoT sensor nodes using nature-inspired methods such as GWO, and SSA. Also, we need to estimate the greatest density of target nodes using precise information about anchor or beacon nodes' position. The proposed algorithms are produced in algorithm 3 and algorithm 4, respectively.

Algorithm 3. Hybrid method (SSA and GWO)

Input: itmax, GWO population X, SSA population Y, Size M, learning factors C1,C2
Output: optimal solution
Function Start
for i=1 : M
    for =1 : R
        initialize SSA population Y
        compute fitness for each agent
        chaotic sequence Generation
    End for (j)
End for (i)
for t = 1 : itmax
for i=1 : M
    for j=1 : R
        compute $x_j^1, \overrightarrow{D_\alpha}, \overrightarrow{D_\beta}, \overrightarrow{D_\delta}$
        compute $\boldsymbol{w1}, \boldsymbol{w2}, \boldsymbol{w3}$
        compute $\boldsymbol{xibest}$
        update position and velocity
    End for (j)
End for (i)
Compute value of fitness function and
Update values of $\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\delta}$

Algorithm 4. Proposed method

Input: Unknown Nodes, Anchor Nodes and Communication Range (R)
Output: Localized Nodes and Error Rates
Procedure Start
Randomly Initialize target nodes with unknown position
Randomly Initialize anchor nodes with known position
For each anchor node (i) with R do
    Calculate the distance from target node (x,y) and anchor nodes within R
    $$\boldsymbol{d_i} = \sqrt{(\boldsymbol{x} - \boldsymbol{x_i})^2 + (\boldsymbol{y} - \boldsymbol{y_i})^2}$$
    Calculate Objective Function
    $$\boldsymbol{f(x,y)} = \boldsymbol{min} \sum_{i=1}^{M} \left(\sqrt{(\boldsymbol{x} - \boldsymbol{x_i})^2 + (\boldsymbol{y} - \boldsymbol{y_i})^2}\right)^2$$
    Calculate Localization Error
    $$\boldsymbol{E_l} = \frac{1}{N_l} \sum_{i=1}^{l} \sqrt{(\boldsymbol{x_i} - \boldsymbol{X_i})^2 + (\boldsymbol{y_i} - \boldsymbol{Y_i})^2}$$
    If all Target Node get localized
        Break
    Else
        Continue
End For

4. RESULTS AND DISCUSSION

4.1. Environmental parameters

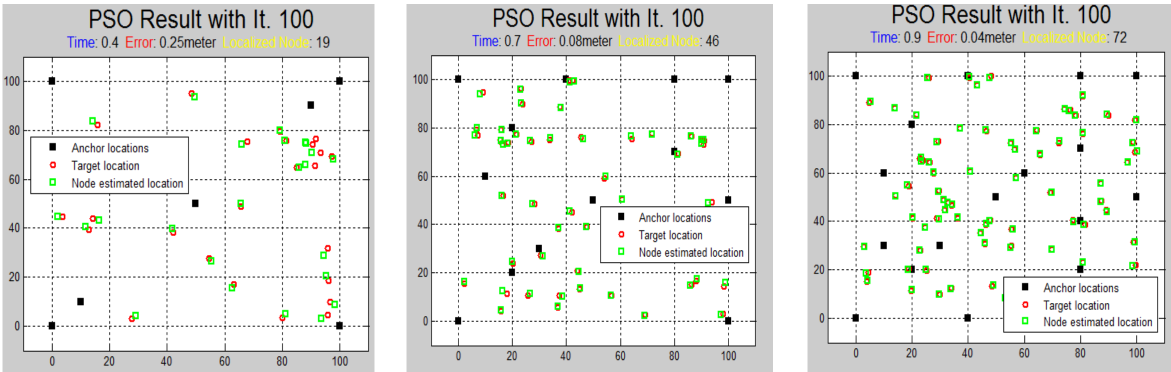
All the measurements of experiments for the three algorithms (PSO, BOA, and proposed algorithm) are implemented using R2019b version of MATLAB on a platform of Windows 10 operating system, Intel Core i7 CPU, and RAM 16 GB. The factors' values of the environment area are displayed in Table 2.

Table 2. Environmental parameters

Factors	Values
Target nodes (i)	$\sum_{i=1}^{4} i * 25$
Anchor or beacon nodes (b)	$target\ nodes/4$
Range of Node transmission (R)	30 m
Environment Area (A)	100 m*100 m
Iteration Numbers (t)	100

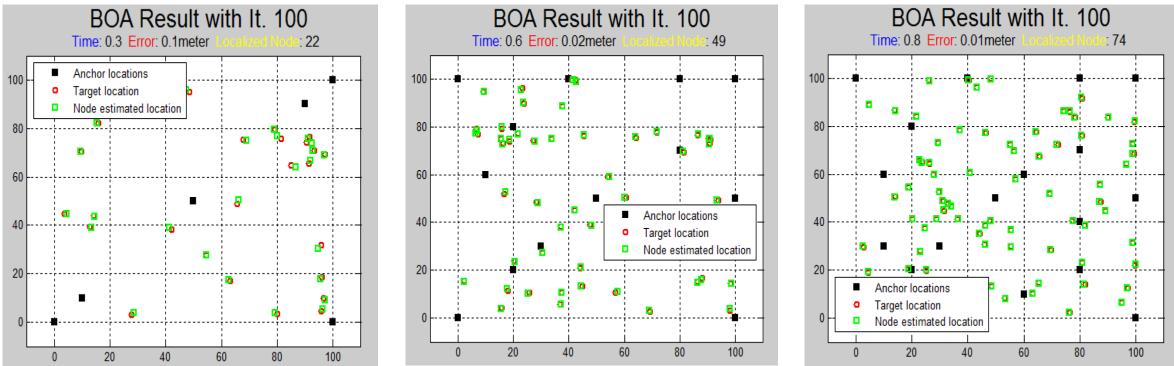
4.2. Experimental results

Many experiments are conducted through this paper. PSO algorithm is implemented with 7, 13 and 19 anchors and with 25, 50 and 75 target nodes as shown in Figure 2. Also, BOA algorithm is implemented with 7, 13 and 19 anchors and with 25, 50 and 75 target nodes as shown in Figure 3. Finally, proposed hybrid algorithm is implemented with 7, 13 and 19 anchors and with 25, 50 and 75 target nodes as shown in Figure 4.



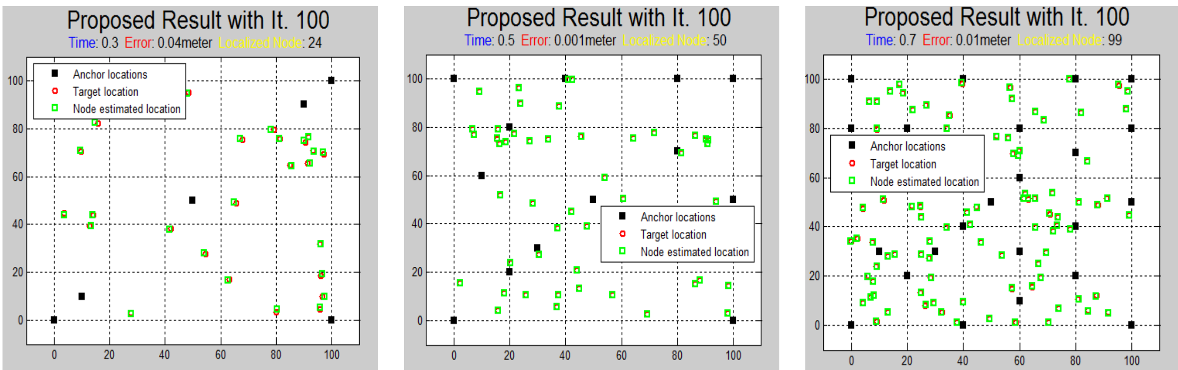
(a) (b) (c)

Figure 2. Experiment 1 using PSO: (a) results of 7 anchors and *25* target nodes, (b) results of 13 anchors and 50 target nodes, (c) results of 19 anchors and 75 target nodes



(a) (b) (c)

Figure 3. Experiment 2 using BOA: (a) results of 7 anchors and *25* target nodes, (b) results of 13 anchors and 50 target nodes, (c) results of 19 anchors and 75 target nodes



(a) (b) (c)

Figure 4. Experiment 3 using proposed GWO and SSA: (a) results of 7 anchors and 25 target nodes, (b) results of 13 anchors and 50 target nodes, (c) results of 19 anchors and 75 target nodes

The results of the above experiments using 7, 13, 19, 25 anchors and 25, 50, 75 and 100 target nodes are displayed in Table 3. Error of localized node in meter (E_L(m)), Time in seconds (Ts) and number of localized nodes (N_L) are displayed also in Table 3. We found form Table 3 that the proposed algorithm achieved highest N_L and lowest E_L than other related works.

4.3. Comparison between proposed algorithm and other related works

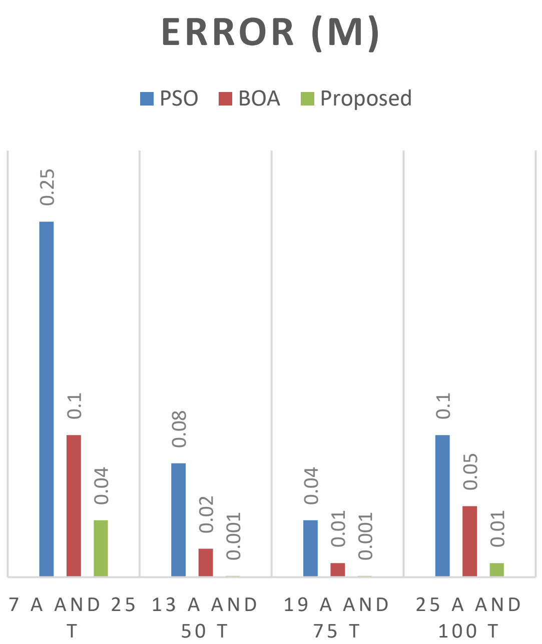
According to the results shown in Tables 3 and 4, we found that the proposed method using the hybrid optimization algorithms (SSA and GWO) achieved higher accuracy and lowest error than other related works. Also, we found that the proposed method achieved low error rate with high number of localized nodes. The error rate (m) and time consumption (s) between proposed method and other related works are represented in Figures 5 and 6 respectively.

Table 3. Results of applying the various localization algorithms where E=Error, T=Time and N=number of localized nodes

Target nodes	Anchor nodes	PSO			BOA			Proposed Algorithm		
		E_L(m)	T(s)	N_L	E_L(m)	T(s)	N_L	E_L(m)	T(s)	N_L
25	7	0.25	0.4	19	0.1	0.3	22	0.04	0.3	24
50	13	0.08	0.7	46	0.02	0.6	49	0.001	0.5	50
75	19	0.04	0.9	72	0.01	0.8	74	0.001	0.6	75
100	25	0.1	1.3	91	0.05	0.9	95	0.01	0.7	99

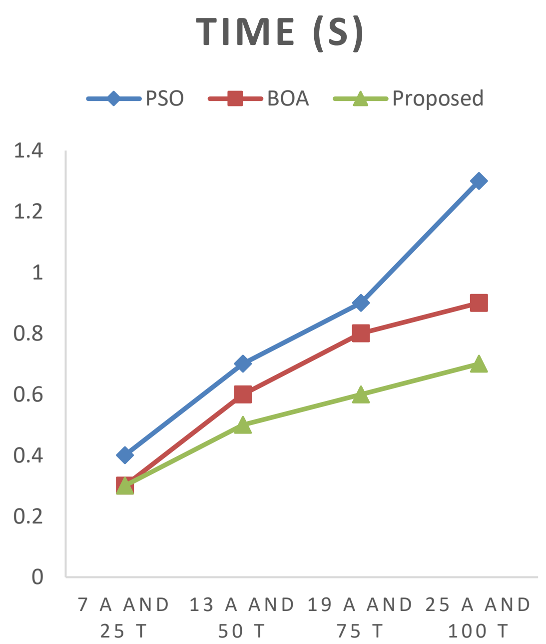
Table 4. Comparison between proposed method and other related works

Reference	Method	Type	Error (m)
[18]	PSO, Genetic and firefly algorithm (FA)	Anchor based-Range based	PSO: 0.1 GA: 0.4 FA: 0.8
[19]	BOA and PSO	Anchor based-Range based	BOA: 0.21 PSO: 0.78
[20]	PSO and GWO	Anchor based-Range based	PSO: 0.30 GWO: 0.658
Proposed Method	SSA and GWO	Anchor based-Range based	0.01



A labeled for Anchors and T labeled for Target

Figure 5. Error chart in meters for each localization algorithm in different experiments



A labeled for Anchors and T labeled for Target

Figure 6. Time chart in seconds for each localization algorithm in different experiments

5. CONCLUSION

In this article, hybrid localization algorithm based on dynamics inspired algorithms (SSA, and GWO) has been proposed and treats node location as an optimization dilemma. The suggested method has been performed and verified in different WSN deployments using various target nodes and beacon nodes. Besides, the proposed algorithm was assessed and compared with known optimization methods, namely PSO and BOA, concerning localization accuracy, computing time and the number of local nodes. The proposed method achieved high accuracy with lower error rate (0.001) and localized high number of IoT nodes.

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