Table 1. Taxonomy of beacon-based localization approaches for sensor nodes in WSN

Parameters	Single beacon-based localization approach [22]	Two beacons-based localization approach [20][21]	Three beacons-based localization approach [19]
Available one beacon node	Work	Fail	Fail
Available two beacon nodes	Work	Work	Fail
Available three beacon node	Work	Work	Work
Dense network deployment	Low	Moderate	High
Computational cost	High	Moderate	Low
Mean location error	Low	Moderate	High
Number of localized nodes	High	Moderate	Low

localization approaches are Distance Vector-Hop (DV-Hop) [16], Ad-Hoc Positioning System (APS) [17], and Multi-Dimensional Scaling (MDS) [18].

In range-based localization approaches, beacon nodes information is required to estimate the coordination of sensor nodes. Beacon nodes are nodes whose coordinate information is known in the system. The localization of sensor nodes requires at least three number of beacon nodes [19]. The cost of beacon nodes in the system is higher than the deployment of sensor nodes due to the additional cost of a Global Positioning System (GPS) equipped with beacon nodes. Localization of two beacons [20] [21] and single beacon nodes [22] occurs in WSNs to reduce the hardware cost of beacon nodes in the system.

Most researchers are concerned about three beacon-based localization approaches compared to two and single based localization systems. Three beacon-based approaches using computational intelligence algorithms [23] present an enormous amount of WSN operational research domains for the localization of sensor nodes. A variety of beacon nodes-based localization algorithms, such as three beacons, two beacons, and single beacon-based localization approaches. Three beacon-based localization approaches consisting of at least three beacon nodes, two beacon-based localization approaches consisting of at least two beacon nodes, and a single beacon-based localization approach consisting of at least one beacon node and two virtual nodes is needed. Single, two, three based localization approaches in WSNs have been compared with network performance standards, as shown in Table 1, and definitions are presented below.

- Number of available beacon nodes:
  The total number of beacon nodes is required to complete the localization of the sensor node.
- Density of the network:
  The total number of sensor nodes is deployed to provide complete coverage of the target area.
- Computational cost:
  The total time required to complete the process of localization of the sensor nodes deployed in the target area. Generally, it is measured in seconds time units.
- Mean location error:
  In the localization process of the sensor nodes, the location error calculated as the average difference between the actual location and the estimated location.
- Number of localized nodes:
  The total number of localized sensor nodes after the completion of the localization process in terms of beacon nodes.

Background

This sub-section of the introduction section describes how well-known computational intelligence algorithms work. Computational intelligence algorithms such as EWO, CSO, and PSO are as follows:

Eurasian Wolves Optimizer (EWO): Mirjalili et al. [24] proposed an EWO algorithm for eurasian wolves' inspired leadership quality. It is a swarm computational intelligence algorithm similar to Particle Swarm Optimization (PSO), Ant Colony Optimization (ABC) algorithm. However, it is far superior to other swarm optimization algorithms. This mimics the lead pecking order and the relationship of wolves, as shown in Figure 1. The social pecking order is simulated by classifying the population of search agents based on their fitness:

- Level 1 (Alpha):
  This is the leader who is male or female. Alpha is mostly responsible for decision making (such as hunting, sleeping places, etc.). Others accept alpha by putting their tails down.
- Level 2 (Beta):
  Betas are subordinate wolves who help alpha in making decisions. Beta is an advisor to alpha of this pack. They consider the best candidate to be an alpha when the alpha dies or becomes too old. Beta ensures alpha's orders are followed and it also provides them with feedback.
- Level 3 (Delta):
  Deltas are also subordinate wolves. Delta wolves dominate Omega and report to alpha and beta. The delta can be classified as follows:
  - Scouts: Responsible for visualizing boundaries.
  - Sentinels: Responsible for protecting the pack
  - Elders: Which were sometimes alpha or beta.
  - Hunters: Supports alpha and beta in hunting.

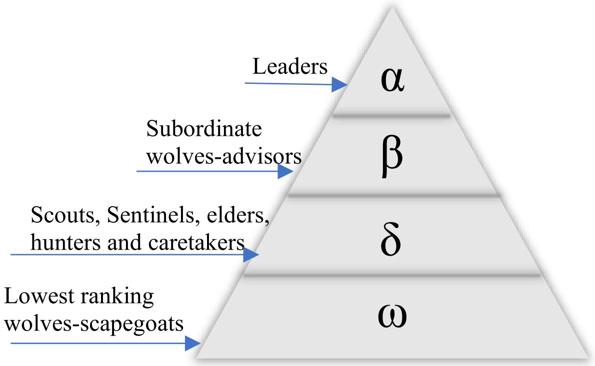

Figure 1. Grey Wolves Optimizer Social Hierarchy

- Caretakers: Responsible for caring for sick, weak and injured wolves
- Level 4 (Omega):
  It is like a sacrificial goat in a pack.

EWO Search Process: The model demonstrated mimic hunting behavior of eurasian wolves to use three stages, searching, circling, and attacking prey. The first two stages are given to the exploration process and the last one presents the exploitation process. EWO saves the first three best solutions and is obliged to modify their location according to the best position of the rest of the search agents.

- Searching (exploration): Finding the prey.
- Encircling (exploration): During the hunting process, they first surround the prey.
- Attacking (exploitation): Usually guided by alpha, beta and delta can play a role according to the situation.

Searching (Exploration): Eurasian wolves typically detect the search process according to alpha, beta, and delta positions. They distributed themselves from one another to exploit to locate prey and attack prey. The EWO algorithm uses the A constraint, in which A is a random value, and its value is greater than 1 or less than -1. The search agents may diverge from the prey when |A| > 1, and they force to diverge for finding a better one.

Encircling (Exploration): Eurasian wolves encircling the prey before hunting. The encircling behavior calculated by using mathematical equations (1) and (2) are as follows:

$$\vec{D} = |\vec{C}.\overrightarrow{X_p}(t) - \vec{X}(t)| \quad (1)$$

$$\vec{X}(t+1) = \overrightarrow{X_p}(t) - \vec{A}.\vec{D} \quad (2)$$

Where t presents the current iteration, $\vec{A}$ and $\vec{C}$ are coefficient vectors, $\overrightarrow{X_p}$ is the prey position vector, and $\vec{X}$ presents the eurasian wolves position vector.

The vector $\vec{A}$ and $\vec{C}$ computed using equations (3) and (4) as follows:

$$\vec{A} = 2.\vec{a}.\vec{r_1} - \vec{a} \quad (3)$$

$$\vec{C} = 2.\vec{r_2} \quad (4)$$

Where $\vec{a}$ is linearly reduced from 2 to 0 in the iterations, and r_1, r_2 are random vectors [0, 1].

Attacking Prey (Exploitation): Eurasian wolves end the hunt when the prey stops moving. In the EWO algorithm, when |A| < 1, then the wolves attack the prey.

Cuckoo Search Optimizer (CSO): Yang et al. [25] have developed a nature-inspired computational intelligence algorithm from cuckoo birds. Cuckoo birds are laying their eggs in another host bird's nest.

The cuckoo search algorithm has three ideal rules:

- At a certain time, each cuckoo bird lays its eggs in a randomly chosen nest.
- The best nesting takes the high quality of eggs to the next levels.
- The probability of a stranger egg between 0 and 1 is calculated from the number of available hosts.

Particle Swarm Optimization (PSO): Kennedy et al. [26] have developed a nature-inspired algorithm from the social behavior of bird flocking or fish schooling. PSO uses Artificial Intelligence (AI) to find optimal solutions to extremely difficult problems. The hypotheses are plotted in the search space along with the initial velocity of random particles. The value of the particles is moving towards the search space by evaluating the fitness value after each iteration. Each particle is updated with two best values, i.e., p_{best} and g_{best}. Each particle is the current position, and the velocity is modified below equations 3 and 4.

$$v_{n+1} = v_n + c_1.\ rand1()\ *\ (\ p_{best,n} - current\_position_n\ ) + c_2.\ rand2()\ *\ (g_{best,\ n} - current\_position_n) \quad (3)$$

$$current\_position[n+1] = current\_position[n] + v[n+1] \quad (4)$$

where current_position[n+1] is a particle position at (n+1) iteration, current_position[n] is a position at n iteration, v_{n+1} is a velocity of particle at (n+1) iteration, v_n is a velocity of particle at (n) iteration, c_1 is a g_{best} acceleration factor, c_2 is a p_{best} acceleration factor, rand1() and rand2() is a random number [0, 1], g_{best} is a swarm position, p_{best} is a particle position.

In this paper, the range-based localization approach was used to design a single beacon-based localization algorithm, in which EW-CSO was formed for the localization of a randomly deployed mobile sensor node using the EWO and CSO computational intelligence algorithms. After a lot of advanced search in the research domain, results come that the EWO algorithm and its hybrid algorithm are still not used with a single beacon-based localization approach. The main contribution of this paper is:

- To propose the implementation of single beacon-based localization approaches using the EWO algorithm.

- EWO with the CSO algorithm is used for the implementation of a single beacon-based localization approach.
- EWO with the PSO algorithm is used for the implementation of a single beacon-based localization approach.

The advantage of the proposed work implementation to provide more accurate and less computation time to localize the mobile sensor nodes. Simulation results of the proposed works in which the EW-CSO algorithm performs better in the mean localization error, computation cost, and number of localized nodes compared with the EWO and EW-PSO algorithms in a single beacon-based localization approach. The computations of EWO and EW-PSO are almost equal in terms of cost when the deployment of mobile sensor nodes with high density in the WSN.

This paper is structured as follows: section two presents a literature survey of respected existing works in the field of beacon-based mobile sensor node localization, section three provides the proposed approach model, flowchart and algorithm, section four provides the proposed work evaluation among them in terms of mean localization error, computation cost, number of localized nodes, and section five present the conclusions of the designed paperwork.

2. Literature Survey

This section provides a critical analysis of the latest research works available in the field of beacon-based localization in WSNs using computational algorithms. The literature survey of the existing work is further classified into two-part; the first part consists of a single beacon-based localization approach and miscellaneous beacon-based localization approaches using computational intelligence algorithms. Miscellaneous beacon-based localization consists of more than single beacon nodes used to localize mobile sensor nodes.

Single beacon-based localization approaches

Singh et al. [22] proposed a single anchor node-based localization of sensor nodes in WSN with the support of Computational Intelligence (CI) algorithms. The CI algorithm reduces hardware requirements for accurate localization of sensor nodes in an application. Only one anchor node is using virtual nodes for precise localization of mobile sensor nodes within its range. Mobile sensor nodes estimate their location, once mobile sensor nodes fall within the scope of two of the six virtual nodes surrounding the anchor nodes. The results of this work experiment showed effective results in terms of the number of mobile sensor nodes localization accuracy and scalability. The problem of line of sight is encountered in harsh environments, that is, minimized by the projection of virtual anchor nodes.

A novel 3D node localization algorithm proposed by Singh et al. [27] with the help of Computational Intelligence (CI) algorithms. CI algorithms such as PSO , H-Best PSO (HPSO), Firefly Algorithm (FA), and Biography-Based Optimization (BBO) are used to estimate the optimal coordinate value of a moving target node using a single reference node/ anchor node in WSN. Each sensor node has heterogeneous properties according to its battery status, and the Degree of Irregularity (DoI) of the radiation pattern is 0.1. The single-node range-based sensor node used three virtual nodes to estimate the 3D position of the mobile target node. Umbrella projection is used to find the 3D projection of the target of the moving node. HPSO and PSO based algorithms are much better performed for the 3D based positioning of target mobile nodes than BBO and FA algorithms.

A novel idea of sensor nodes localization based on moving single anchor node is proposed by Singh et al. [28] using CI algorithms such as PSO and H-best PSO (H-PSO). The Hilbert trajectory follows the mobile anchor node. The only single anchor node used as a reference node to localize the entire sensor node in the WSN. The proposed algorithm minimizes the Line of Sight (LOS) problem with the help of virtual anchor nodes. The H-PSO algorithm has much better accuracy and convergence rate than the PSO algorithm.

Two-way planning models using mobile anchor nodes in WSNs localize sensor nodes, and they are linear mesh scanning and triangular mesh scanning. The work objective proposed by Kaur et al. [29] to provide a model for unused nodes localization with high accuracy and convergence rate in all types of scenarios. The single mobile anchor node uniformly finds different reference points to locate the unsettled sensor nodes in the network area. The proposed work is simulated and evaluated compared to traditional works, and its results are shown in terms of high accuracy and coverage.

Singh et al. [30] provided review chapter work in the field of CI techniques for the localization of sensor nodes in static and dynamic WSNs. The latest emerging work in the area of sensor nodes localization in WSNs is presented in this paper. Various connectivity, range-based, mobility-based localization techniques for sensor nodes were discussed. For optimization, these CI algorithms, such as PSO, BBO, FA, estimate coordination of sensor nodes with Genetic Algorithm (GA), and their results in various scenarios are discussed.

Miscellaneous beacon-based localization approaches

Tuba et al. [31] proposed two-stage sensor node localization using a firefly algorithm. In the WSN, the RSSI (Received Signal Strength Signal) propagation model is used to estimate the distance between the anchor nodes and the semi anchor nodes. The proposed algorithm for the localization of the sensor node follows a two-part: first, four anchor nodes are placed at the corners of the target area coverage and secondly the estimation of the optimal distance using distance calculation. The future direction of this work for an optimal approach for localization of sensors with firefly algorithm modification and adjustment.

Monarch butterfly optimization algorithm used by Strumberger et al. [32] to solve the NP-hard problem of WSN localization. The novel Monarch Butterfly Swarm intelligence approach uses multi-phase localization for sensor nodes. Monarch butterfly optimization is implemented and

Table 2. Taxonomy of single beacon-based localization approaches using computational intelligence algorithms for sensor nodes in WSNs

Authors	Year of Publi-cation	Design approach	Techniques use	Compared approaches	Target parameters	Simulation Tool
Singh et al. [22]	2018	A single anchor-based moving target sensor node localization using CI	Projection of virtual anchor nodes, Bio-inspired localization	HPSO, BBO, FA	Accurate location, Fast convergence, Non-line of sight	MatLab
Singh et al. [27]	2017	A single anchor-based moving target sensor nodes 3D localization in WSN	Bio-inspired localization	PSO, HPSO, BBO, FA	Mean localization error, Highest localization error, Lowest localization error	MatLab
Singh et al. [28]	2018	A single mobile anchor node-based optimized localization in WSN	Bio-inspired localization	PSO, HPSO	Average localization error, Convergence time	MatLab
Kaur et al. [29]	2019	The mesh path planning algorithms-based localization using a single mobile anchor node	Linear mesh scanning, Triangular mesh scanning	DV-hop, Ahmad et al. [38]	Localization error coverage	MatLab
Singh et al. [30]	2019	Review work for computational intelligence algorithms for static and dynamic WSNs	Bio-inspired localization	GA, PSO, BBO, FA	Total overhead communication, total consumption power, total time convergence, algorithmic complexity	MatLab

tested on several problem examples that are found in the literature. Experimental result analysis of the proposed work from other approaches has been successfully presented and has shown considerable potential in terms of solving the NP-hard problem of WSN localization.

A location-aware mobile anchor (MA) uses path planning to optimize mobile nodes. The work of MA to traverse into the target region of interest to minimize localization error and maximize localization of the successful node. Alomari et al. [33] proposed two novel dynamic movement approaches that provide the obstacle avoidance path planning for mobile node localization in WSN. Movement planning of mobile nodes designed based on two swarm intelligence-based algorithms, i.e., GWO and Whale Optimization Algorithm (WOA). Comparing this proposed approach to the snake-like and z-curve models, it has shown remarkable results in terms of localization ratio, localization accuracy, and computation time.

An Elephant Herring Optimization (EHO) algorithm is adopted by Strumberger et al. [34] to solve localization problems in WSN. New metaheuristic computational intelligence approach dealing with NP-hard problems to achieve a near to target coordination value. The purpose of this approach is for the localization of randomly deployed sensor nodes in the monitoring area. The implementation of EHO for node localization in a WSN and results in efficient metaheuristic approaches to deal with sensor nodes localization. The work presents a future direction of the EHO algorithm that can apply to efficient solutions to the superset problem of node localization, i.e., the coverage problem in WSNs.

Table 3. Taxonomy of miscellaneous beacon-based localization approaches using computational intelligence algorithms sensor nodes in WSNs

Authors	Year of Publication	Design approach	Techniques use	Compared approaches	Target parameters	Simulation Tool
Tuba et al. [31]	2018	FA-based sensor nodes localization in two-stage	Semi-mobile nodes, Firefly optimization algorithm	3D Localization, PSO Algorithm, (TLP), BA	Improve localization accuracy	MatLab
Strumberger et al. [32]	2018	Sensor nodes localization using Monarch butterfly optimization algorithm in WSN	Monarch butterfly optimization	PSO, MPSO, ABC, MSABC, MBO	2.5% of anchor nodes with (20 m 50 m), 10% of anchor nodes with 50m	MatLab
Alomari et al. [33]	2018	To obstacle avoidance for mobile anchor nodes using swarm intelligence optimization algorithms	EWO, WOA	Snake-like, Z-curves	Localization ratio, Localization error, Computation time	MatLab
Strumberger et al. [34]	2018	WSN localization using EHO algorithm	EHO algorithm	PSO, Multi step PSO, ABC, Multi step ABC	Mean squared error	Experim-ental setup
Rajakumar et al. [35]	2017	EWO algorithm for node localization problem in WSNs	EWO	PSO, MBA	Computation time, minimum localization error, localized nodes	MatLab
Strumberger et al. [36]	2019	A node localization in WSNs using EHO and tree growth algorithm	EHO algorithm, tree growth algorithm	Iterative best performance algorithm, taboo search, largest absolute difference algorithm, weighted superposition attraction	Localized number nodes, localization error, execution time	--
Tan et al. [37]	2019	A sensor node localization using distance mapping algorithm	DMA, optimized linear transforming function, GA	DV hop, MDS map	Localization error, Total consumption of energy	Network Simulator

Rajkumar et al. [35] proposed work by incorporating the Grey Wolf Optimization (GWO) algorithm to detect the accurate geographic location of unknown sensor nodes with the help of anchor nodes in WSNs. The GWO algorithm mimics the social behavior of a grey wolf leadership to attack targets. The suggested work is implemented using the MatLab tool for randomly deployed sensor nodes in the target region. Parameters such as computation time, localized node percentage, minimum number of error measures for analysis of GWO's ability,

and other types of metaturistic algorithms. The result of faster convergence and success rate of the GWO algorithm is better than other PSO and other metaheuristics algorithms like the Modified BAT algorithm (MBA).
An improved version of metaheuristic algorithms, such as the tree development algorithm and the EHO algorithm, is proposed by Strumberger et al. [36] to solve the localization problem of WSNs. The improvement of the proposed algorithm is analyzed by varying the size of the sensor network from 25 to 150 target nodes. The state of the art of some swarm intelligence algorithms is tested in comparison to the proposed algorithm. Simulation results indicate that the proposed algorithm achieves very efficient results in terms of accurate location estimation of the coordinate of the unknown sensor node.
A distance mapping algorithm (DMA) is proposed by Tan et al. [37] to overcome the node localization problem in WSN. To detect node position with high accuracy using the estimation matrix, distance matrix, and optimized linear transformation function. GA is employed for the optimal detection coordinate value of nodes during the calculation of the proposed algorithm. The node localization approach was simulated using three anchor nodes by the researcher in the laboratory. The results of the proposed algorithm perform well in terms of localization accuracy and energy consumption other than the localization algorithm.
Current important works of literature in the field of beacon-based localization WSNs based on various parameters such as authors' publication, design approach, technique use, comparison approach, target parameters, and simulation tools. Table 2 and Table 3 show the taxonomy of a single and miscellaneous beacon-based localization approach using computational intelligence algorithms.
After a critical analysis of the presented literature works, the localization of sensor nodes became a vital challenge of WSN. Due to the unpredictable behavior of the sensor node, the localization approach became an NP-hard problem. To solve these various computational intelligence algorithms, localization approaches are used to estimate the optimal solution. In section, the presented literature survey paper concern about the three-beacon based location, and they are trying to improve the measured position of sensor nodes using computational intelligence algorithms such as PSO, BBO, FA, Artificial Bee Colony (ABC), Bat Algorithm (BA), EWO, etc. EWO is the smartest computational intelligence optimization algorithm compared to other computational intelligence algorithms. But still, EWO, EW-CSO, and EW-PSO are not used in single beacon-based localization approaches. However, this paper is trying to apply the EW-CSO algorithm to a single node-based localization approach and provides simulation analysis of the results based on the mean localization error, computational time, and number of local nodes.

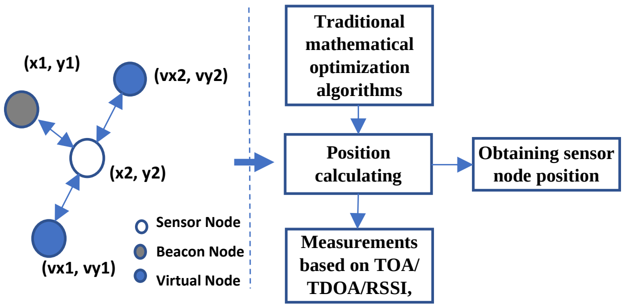

Figure 2. Single beacon-based mobile sensor nodes localization using traditional mathematical optimization algorithm in WSN

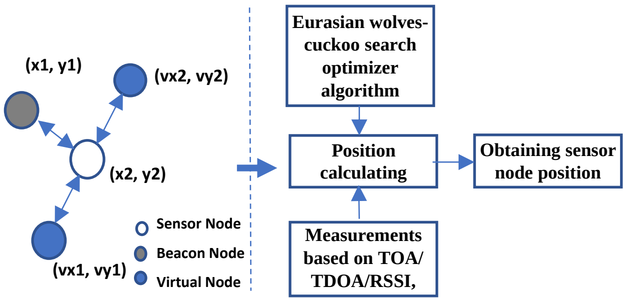

Figure 3. Single beacon-based mobile sensor nodes localization using EW-CSO Algorithm in WSN

3. Localization Problem Formulation

The proposed work design for the formation of mobile sensor node position estimation challenges in a single beacon-based localization approach using computational intelligence algorithms is presented. The localization problem formulation is further classified into a subsection of the proposed model, the proposed flow chart, and the proposed algorithm.

Proposed Model

The proposed model was built with the components of beacon sensor node (x1, y1), sensor node (x1, y2), virtual nodes ((vx1, vy1), (vx2, vy2)), computational intelligence algorithms (EW-CSO) and measuring techniques (RSSI) as the inputs for the positioning estimation of sensor nodes. The traditional optimization-based localization model using PSO, BBO, FA, ABC, BA, and GA is shown in Figure 2. New smart localization model for single-based localization using the EW-CSO algorithm, as shown in Figure 3.

Proposed Flow Chart

The working principles of the proposed work are depicted as a flow chart in Figure. 4, which illustrates the flow control of a framework designed to localize mobile sensor nodes in a single beacon-based approach using computational intelligence algorithms. Computational

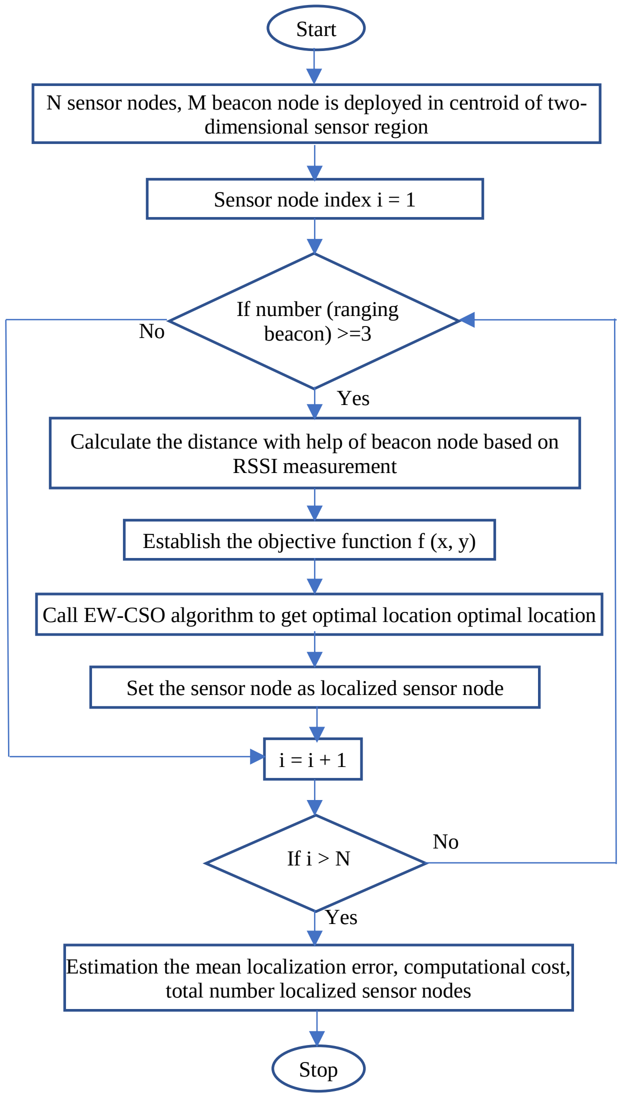

Figure 4. Flowchart of single beacon-based mobile sensor nodes localization using the EW-CSO algorithm in WSN.

intelligence algorithms are used to find optimal localization in EWO, EW-CSO, and EW-PSO algorithms.

Proposed Algorithm

The proposed algorithm is designed for single beacon-based localization using EW-CSO computational intelligence algorithms. Algorithm for EW-CSO for localization of mobile sensor nodes present below:

Inputs:

$Target_{area}$ is a given target area where mobile sensor nodes are to deploy randomly, l is a length and b is a breath of the target area, BN (x, y) in beacon nodes coordinate, centroid (a, b, c, d) is a function to calculate the centroid of the given area and a, b, c, d are the sides of the given target area, MN (x, y) is a current location of mobile nodes, SN_{total} is a total number of mobile sensor nodes, dim is represent the dimensional of the target area, i is denoted the index of mobile sensor nodes, SN_{ref} calculates the total number of beacon nodes are in their range, $dist_i$ is estimating the distance between sensor nodes and beacon nodes, the position is to save the best location of optimization algorithm in each iteration, Max_{iter} represents the maximum of iteration to position refinement, SearchAgent is agents are required to finding an optimal position, lb is a lower bound and ub is an upper bound of the given target area.

Begin:

1. $Target_{area}$= l * b
2. BN (x, y) = centroid (a, b, c, d)
3. MN (x, y) = $Target_{area}$ * rand (SN_{total}, dim)
4. for i =1 to SN_{total}
5. do
6. SN_{ref} =$RSSI_{recvied}$(BN)
7. If (size (SN_{ref})<= three))
8. then
9. Distance between beacon nodes and mobile sensor node is calculated using below equation:
10. $dist_i = \sqrt{((x_t - x)^2 + (y_t - y)^2)}$
11. Estimate the coordinate value of SN (x, y, z) using below equations:
12. let's z=0 for two-dimensional area
13. $(x-x_1)^2 + (y-y_1)^2 + (z-z_1)^2 = dist_1^2$
14. $(x-x_2)^2 + (y-y_2)^2 + (z-z_2)^2 = dist_2^2$
15. $(x-x_3)^2 + (y-y_3)^2 + (z-z_3)^2 = dist_3^2$
16. Call Eurasian Wolves Optimizer computational intelligence algorithm:
17. Initialize the alpha, beta, delta position using below equation
18. Positions=initialization (SearchAgents_no, dim, ub, lb)
19. while (1 < Max_{Iter})
20. do
21. The fitness value of alpha, beta and delta is calculated
22. Update the position of search agents
23. Call Cuckoo Optimizer for an alpha, beta, and delta
24. The final position is calculated from the below equation:
25. Position= (alpha+ beta+ delta)/ 3;
26. End while
27. End if
28. End For

4. Simulation Results and Analysis

Performance analysis of the proposed EW-CSO algorithm with comparative analysis of EWO and EW-PSO algorithms in a single beacon-based localization approach.

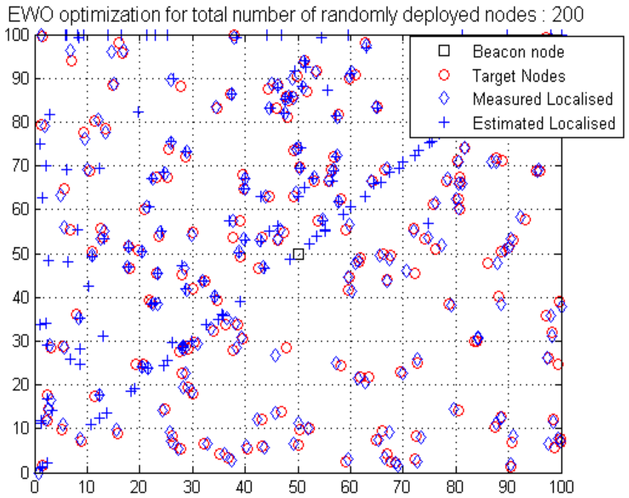

Figure 5. EWO algorithm for randomly deployed mobile sensor nodes located in the target area

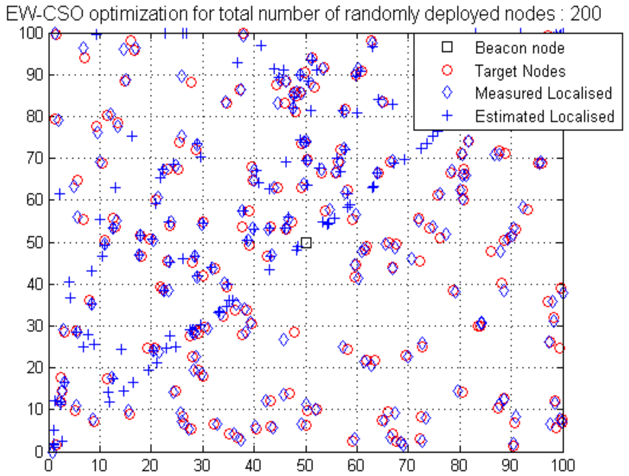

Figure 6. EW-CSO algorithm for randomly deployed mobile sensor nodes located in the target area

The performance is analyzed with the help of Matlab software on a PC with an Intel Core i7 processor, 3.40 GHz CPU and 4 GB of RAM. This section is divided into two parts, such as the simulation scenario and performance evaluation criteria.

Simulation Scenario

In the simulation configuration, the transmission range of beacons and mobile sensor nodes is fixed at 50 m. Random deployment of mobile sensor nodes in the target area of 100 x 100 m^2. The beacon node is deployed in the center of the target area, and the free space path loss and fading model is considered. The RSSI measurement technique is used to distance estimate between mobile sensor-nodes and beacon nodes in a range-based localization approach. The optimization algorithm takes EWO, EW-CSO, and EW-PSO into the simulation of a single beacon-based localization approach. In the optimization algorithm, the search agents are 10, and the maximum iteration for the estimate location refinement is set to 25 times.

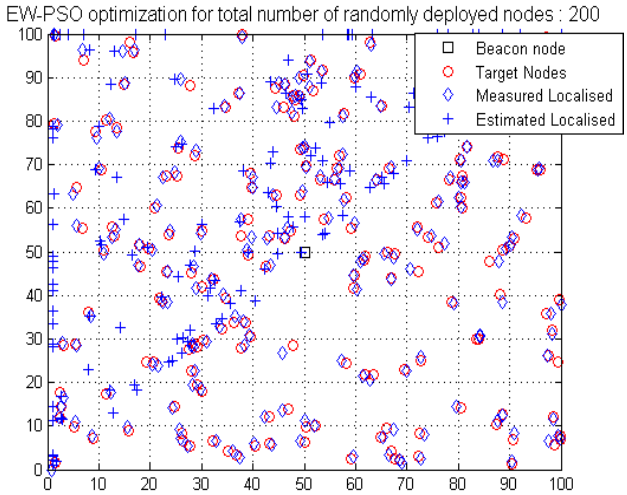

Figure 7. EW-PSO algorithm for randomly deployed mobile sensor nodes located in the target area**.**

Performance Evaluation Criteria

The performance evaluation criteria for a single beacon-based localization approach using the EW-CSO algorithm are mean localization error, computation cost, and number of sensors localized with the variation of the number of randomly deployed sensor nodes. In each simulation with a variation of the sensor nodes deployed from 10 to 200 with a difference of 10. The single beacon-based localization approach, using the EWO, EW-CSO, and EW-PSO algorithms, is shown in Figure 5, Figure 6, and Figure 7 for randomly deployed of 200 mobile sensor nodes.

- Mean Localization Error:
  The average difference between the actual sensor node and the estimated sensor node position. Mean localization error calculation, with a difference of 10 in each simulation with a variation of mobile sensor nodes deployed from 10 to 200, as shown in Figure 8. The resulting graph shows that the EW-CSO algorithm is much better than the EWO and EW-PSO algorithms for a single beacon-based localization approach.
- Computational Cost:
  The total time required to complete the process of localization for mobile sensor nodes is known as the computation cost and is typically measured in terms of seconds (seconds) unit. The computational cost of single beacon-based localization using the EW-CSO algorithm approximately lesser than compared to the EWO and EW-PSO algorithms. In each simulation, with a difference of 10 to 200 deployed mobile sensor nodes, the cost of the computation is shown in Figure 9.
- Number of Localized Nodes:
  The number of sensor nodes localized on the number of randomly deployed mobile sensor nodes by a variation of 10 to 200 mobile sensor nodes with a difference of 10 to 200 sensor nodes with a difference

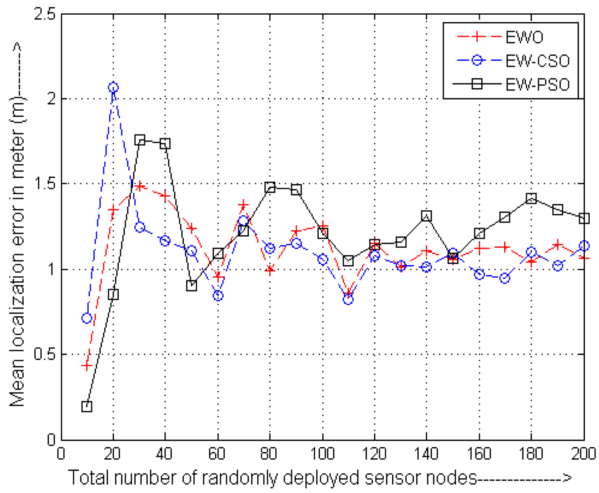

Figure 8. The mean localization error required for mobile sensor nodes localized in the target area.

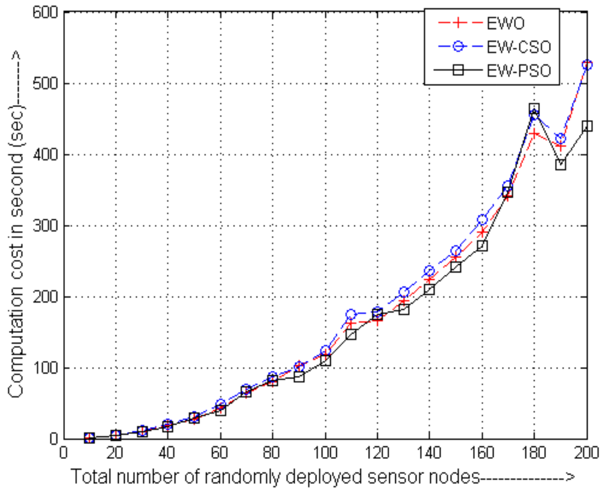

Figure 9. The total computational cost required for mobile sensor nodes localized in the target area.

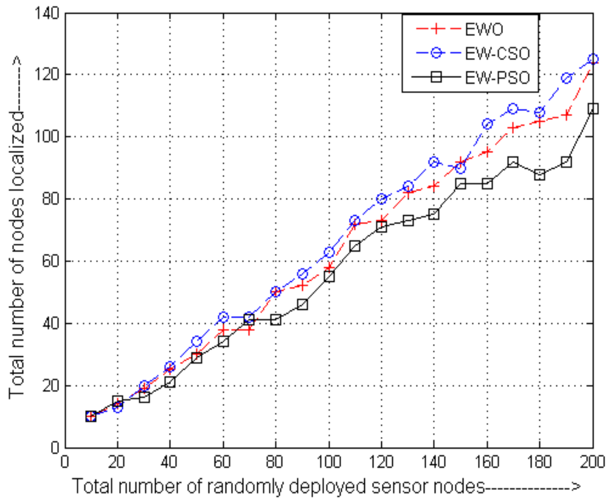

Figure 10. The total number of mobile sensor nodes localized in the target area.

of 10. The number of mobile sensor nodes localized using a single beacon-based localization approach with the EW-CSO algorithm is better than compared to EWO and EW-PSO algorithms, as shown in Figure 10.

5. Conclusion

The localization of the mobile sensor node poses a significant challenge for WSN. Technology advancement leads to WSN-IoT integration to minimize human intervention. To minimize the additional cost of GPS components using a beacon-based localization approach is also minimized. The mobile sensor computes the optimal coordinate value using the EW-CSO algorithm in this paper. The simulated results and analysis of the EW-CSO algorithm are compared with the EWO and EW-PSO algorithms in a single beacon-based localization approach. The EW-CSO algorithm performs much better than the EWO and EW-PSO algorithms in terms of mean localization error, computation cost, and number of localized nodes. This approach also reduced the line of sight problem with the efficient use of hardware resources. The future direction of this proposed work can be applied to the three-dimensional target region.

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