Self-Improved Jellyfish Optimization for Extending Coverage in WSN

[1]Swati, [2]Sujata V. Mallapur

[1]Asst. Professor, Artificial Intelligence & Machine Learning at Sharnbasva University, Kalaburagi.

[2]Professor & Research Dean in the department of Artificial Intelligence & Machine Learning, Sharnbasva University, Kalaburagi

Abstract- Recently, the vast advantages in networking technology paves its way in various arena. In WSN, the network consists of spatially distributed sensor nodes with base stations. In real-time, the sensors in WSN monitors physical and environmental conditions including temperature, pressure, etc. The sensor nodes in the network are functioned as router and originator. In WSNs nodal coverage problem is one of the major problem. This issue limited the sensing coverage of nodes while monitoring or tracking specific conditions. That's why this work is intended to solve this issue using coverage optimization. This work is supposed to propose a novel efficient node coverage model for WSN using 2D distance evaluation in accordance with weighted Minkowski distance. Consequently, the optimal positioning of sensor nodes is determined by proposed SIJSO algorithm. Here, the proposed SIJSO algorithm for optimal positioning of sensor nodes is an implemented version of traditional JSO algorithm. The traditional JSO algorithm is a nature-based metaheuristic algorithm which mimics the behavioral aspects of jellyfish. In the conclusion, this proposed work proved its efficiency through various analysis.

Keywords: wireless sensor networks, nodal coverage, weighted Minkowski distance, circle chaotic map and SIJSO.

Nomenclature

ABBREVIATION	DESCRIPTION
ACR	Area Coverage Reliability
BPA	Basic Probability Assignment
CHA	Convex Hull Attraction
DST	Dempster-Shafer Theory
HWSN	Heterogeneous Wireless Sensor Network
LOA	Lion Optimization Algorithm
QUEC	reinforcement learning-based UAV Enhanced Coverage
JSO	Jellyfish Search Optimizer
SIJSO	Self-Improved Jellyfish Search Optimizer
UAV	Unmanned Aerial Vehicle
WSN	Wireless Sensor Network
HHO	Harris Hawks Optimization
NBO	Namib Beetle Optimization

1. INTRODUCTION

Edge computing and information-centric wireless communication are becoming more and more common in 5G and the IoT as a result of the advancement of communication technology. Examples of them frequently used include wireless sensor networks [1]. The IoT devices are centered about a dispersed base station, and each node uses wireless data communication to share information with the other nodes. Sensor nodes, small devices, and other devices make up WSNs, which are multi-hop self-organizing networks. WSNs monitor activities in a specified region and transmit the gathered data to a data center for processing [6] [15].

Due to variations in the sensing, communication, and processing rates of the nodes, heterogeneous wireless sensor networks frequently arise in real-world wireless sensor network application situations [12]. HWSNs are becoming a main emphasis in ecological environment monitoring, agricultural research, military research, and disaster assistance as communication and software technologies progress [8] [10].

While WSNs concentrate on power saving to increase network longevity, conventional networks are more concerned with improving metrics like throughput and latency [9]. For the WSNs' ability to provide a high level of service, connectivity and coverage are two key problems. Coverage may be used as a metric for sensor network quality of service [14]. Therefore, two key indicators for assessing network quality are coverage and energy use [11]. The calibration of devices, environment monitoring, and exposure are all topics covered by the quality of service sensing component of the quality of service model. So, to eliminate this issue this work is intended to propose a novel nodal coverage approach [13].

2. LITERATURE REVIEW

In 2021, Qiang Liu [1] defined a belief-degree of sensing solution in accordance with DST to introduce a system based on belief-degree-coverage. The proposed model analyzed the reliability of coverage by defining three indices. The solutions of sensing was obtained from calculating BPA of sensing solutions using a membership function and determined the mathematical expression for BPA of interference sources. The above mentioned three indices were analyzed by two algorithms. Based on interference, the perimeter coverage algorithm was introduced and another algorithm was based on Monto Carlo simulation. In which the second algorithm was used to estimate the system parameters influence on network coverage reliability and to compute reliability of network coverage.

In 2021, Xinmiao Lu*et al.* [2] proposed an approach based on fixing priority named improved gap fixing. The proposed improved gap fixing approach was intended to define and prioritize the coverage gap fixing points using Voronoi polygons. Here, the introduced Voronoi polygons was utilized to fix the mobile nodes in the coverage gaps. Then, the overlapped sensing nodes in the network were detached from the network coverage which was done to eliminate the redundancy of the network. The proposed approach has improved network coverage which was proved from obtained simulation results.

In 2022, Li Li and Hongbin Chen [3] presented two algorithms namely CHA algorithm and QUEC algorithm and were utilized for creating a target barrier and for covering targets using reinforcement learning respectively. In which, the CHA algorithm partitioned the targets into clusters and then created a target barrier for clusters where the failed sensors were replaced by redundant sensors. The QUEC algorithm planned the path of UAV to cover the target that were most likely to breach the data in the sensor nodes. Its simulation results were analyzed with several coverage algorithms and resulted that the proposed CHA algorithm limited the use of sensors for the construction of target barrier and extended its lifetime. Likewise, the proposed QUEC algorithm provided with increased energy efficiency and breaching target detection as well as deduced coverage completion time of UAV.

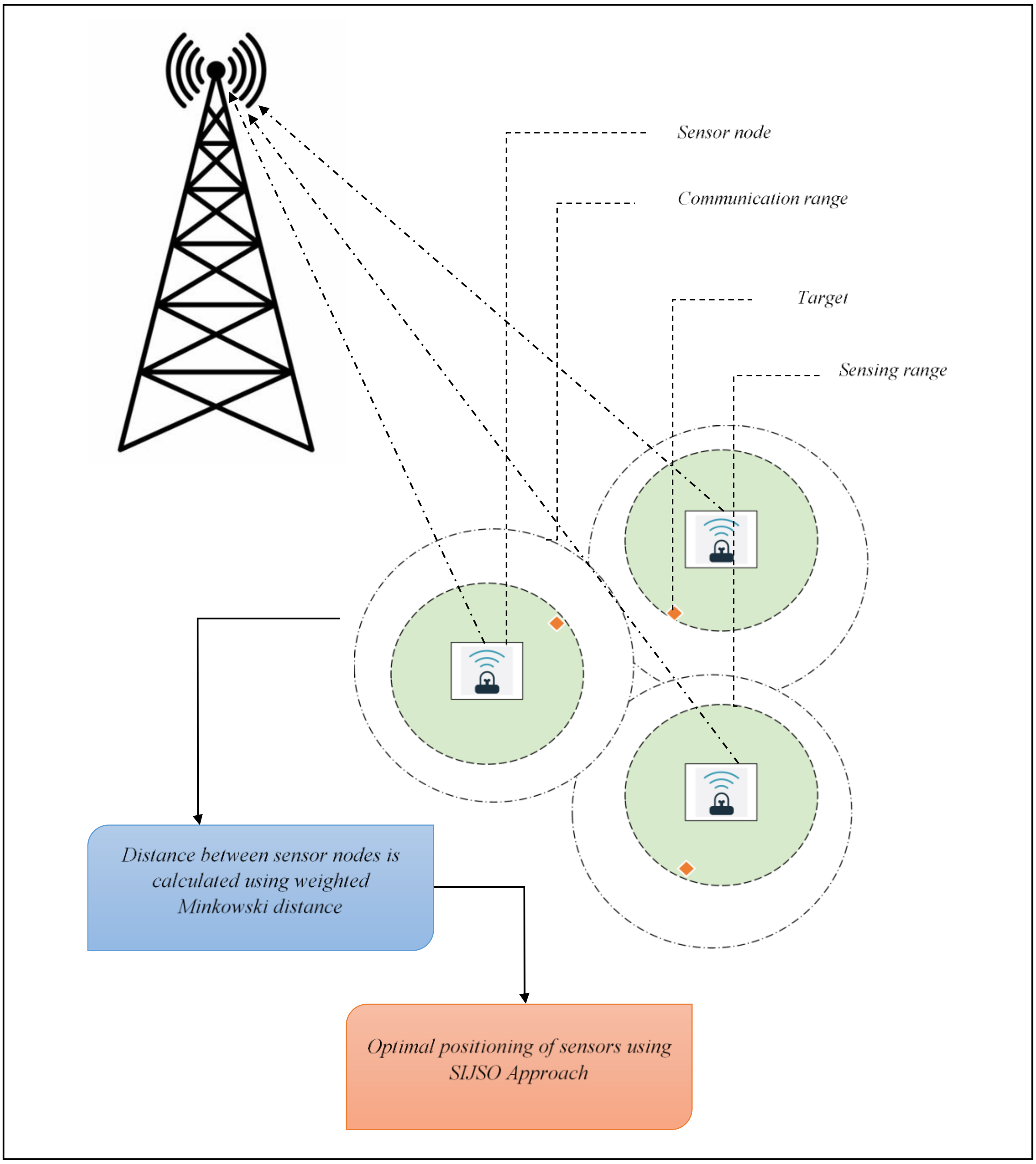
In 2023, Pingzhang Gou*et al.* [4] proposed a technique based on K-means clustering algorithm and 3D-Voronoi partitioning which was an enhanced energy efficient coverage technique by maintaining lo number of sensor nodes while ensuring the network coverage. The sensor nodes were randomly organized for two times by caustic polynomial mutation mechanism to enhance node stability. Subsequently, K-means algorithm and 3D-Voronoi partitioning was used to evaluate optimum perceptual radius for improving the quality of network coverage. Further, lowered energy consumption and longer lifetime was provided by proposing two strategies named polling working and multi-hop communication. The simulation results of this work effectively proved that it has enhanced network lifetime and network coverage.

In 2020, Suparna Chakraborty*et al.* [5] designed an approach based Monto Carlo simulation to calculate the impact of energy-based data transfer capability on ACR and energy drained sensor nodes. This simulation based approach utilized energy matrix which exposed the required energy for data transmission among neighbor nodes, residual energy of nodes, multi-state nature and connectivity of sensor nodes.

3. SUMMARIZED DESCRIPTION ON SIJSO FOR EXTENDING NODE COVERAGE IN WSN

This work is supposed to propose a novel efficient node coverage model for WSN using 2D distance evaluation in accordance with weighted Minkowski distance and the framework is depicted in **Figure 1**. Consequently, the optimal positioning of sensor nodes is determined by proposed SIJSO algorithm. Here, the proposed SIJSO algorithm for optimal positioning of sensor nodes is an implemented version of traditional JSO algorithm. The traditional JSO algorithm is a nature-based metaheuristic algorithm which mimics the behavioral aspects of jellyfish. Thereby, the proposed model's functioning are as follows.

Figure 1: Framework of proposed SIJSO approach for nodal coverage expansion



Consider a 2D WSN region with *m* number of randomly positioned nodes in an area $a \times b\ m^2$. A descriptive set of nodes are denoted by $N = \{N_1, N_2, N_3, ..., N_m\}$ and the *x* and *y* coordinates of every node N_a are denoted by (x_a, y_a) where, $a = 1, 2, 3, ..., m$. The network model for a 2D WSN region is shown:

1. The sensor node in the network is considered as a uniform sensor because of its similar communication abilities, topology and model parameters as others.
2. Every sensor node in the network are installed with better communication ability, sufficient energy and timely-access to sensed data.
3. Each sensor nodes can move its position independently in the network and simultaneously it could update its position data.
4. The communication and sensing radius of each sensor node is denoted by CR_N and SR_N. Both are measured in terms of meter (m) and the sensing radius of sensor node is twice as communication radius of senor node $(CR_N \geq 2SR_N)$.

Generally, the sensing range of node is covered in a spherical region, as node positioned in the center and its radius be SR_N. In 2D WSN region, let us consider target points as T, the set of target points as $T = \{T_1, T_2, T_3, ..., T_n\}$ and position coordinates of each target point T_b as (x_b, y_b) where, $b = 1, 2, 3, ..., n$. Each target point T_b coverage of sensor nodes is determined by whether the distance between targeted point T_b and any of the sensor node is lesser than or equal to sensing radius SR_N.

Conventionally, the distance between a sensor node N_a and a target point T_b is evaluated by Euclidean distance formula which is shown in Eq. (1).

$$D(N_a, T_b) = \sqrt{(x_a - x_b)^2 + (y_a - y_b)^2} \tag{1}$$

While, in this proposed model the distance between a sensor node N_a and a target point T_b is computed using weighted Minkowski distance. Generally, the weighted Minkowski distance is a simplified form of Euclidean distance and it is used as a measurement to compute n-dimensional real-space where distances can be assigned as vectors. Thereby, the computed weighted Minkowski distance between N_a and T_b is formulated in Eq. (2).

$$D(N_a, T_b) = \left\{ \sum_{a=1}^{m} \sum_{b=1}^{n} W \left| N_a - T_b \right|^z \right\}^{1/z} \tag{2}$$

In this proposed work, the node sensing framework utilizes a strategy named Boolean sensing which means the probability of the target point T_b is obtained as 1 if the value of sensing radius SR_N is greater than or equal to $D(N_a, T_b)$ otherwise its probability is returned as 0. If the probability of target point T_b to be sensed is cover-up by sensor node SR_N be *z* and it is expressed in Eq. (3).

$$z(N_a, T_b) = \begin{cases} 1, & SR_N \geq D(N_a, T_b) \\ 0, & SR_N < D(N_a, T_b) \end{cases} \tag{3}$$

The sensor nodes in considered 2D WSN region are mutually functioned with each and every nodes. It means that any target point in a region can be covered by more sensor nodes concurrently. This results in the mutual sensing of probability of target point T_b which is represented in Eq. (4).

$$Z\left(N_a,T_b\right)=1-\prod_{a=1}^{m}\left(1-z\left(N_a,T_b\right)\right) \tag{4}$$

Further, the rate of coverage of each sensor node in a 2D WSN region is mathematically expressed in Eq. (5).

$$C=\frac{\sum_{b=1}^{n}Z\left(N_a,T_b\right)}{a\times b} \tag{5}$$

Based on above computations, the problems related to node coverage in WSN could be solved by ILP model as shown in Eq. (6) and Eq. (7).

$$Max\,C=\frac{\sum_{b=1}^{n}Z\left(N_a,T_b\right)}{a\times b} \tag{6}$$

$$such\ that\begin{cases}\sum_{b=1}^{n}Z\left(N_a,T_b\right)\geq 0 & 1\leq b\leq n\\ \sum_{b=1}^{n}Z\left(N_a,T_b\right)\leq a\times b & 1\leq b\leq n\\ D\left(N_a,T_b\right)\leq SR_N & 1\leq a\leq m,1\leq b\leq n\end{cases} \tag{7}$$

The coverage of sensor node expressed in Eq. (5) is referred as objective. In which the maximum rate of coverage is needs to be solved, *a*th sensor node is referred as N_a and *b*th target point is referred as T_b and the size of region is represented as $a\times b$.

If the deployed sensor node size is relatively larger then is has more time to solve network coverage problem using ILP model. By the use of ILP model in network coverage problem, the best coverage solution will be obtained. Besides, this work is efficiently work on problem solving by a novel metaheuristic algorithm in a specified time.

3.1 Optimal Positioning of WSN Nodes using Proposed SIJSO Algorithm

The expansion of nodal coverage in WSN is achieved by an objective specified in Eq. (6). The better coverage of nodes is ensured by optimizing the positions of sensor nodes. This can be done by proposed SIJSO algorithm which is adaptation of JSO algorithm [6]. Jellyfish is a creature which lives in ocean with wide varieties of shapes, sizes and colors. The proposed SIJSO algorithm imitates the search and movement behavior of jellyfish as mathematical expressions to solve coverage problem in WSN.

The procedures needs to be followed while proposing this algorithm are as follows:

- A strategy named 'time control strategy' is followed to govern the switching between movements such as moving of jellyfish inside the swarm and moving of jellyfish while following ocean current.
- The movement of jellyfish in search of food will be greater in the place of large amount of food.
- Based on position and its respective objective function, the quantity of food found is determined.

3.1.1 Ocean Current

Each jellyfish in the ocean are considered as vectors. Here, the average of all each jellyfish (vectors) to jellyfish which is positioned in the best position is used for the determination of ocean current direction *d*. therefore, the expression for ocean current direction is shown in Eq. (8).

$$d = \frac{1}{np}\sum d_a \quad (8)$$

$$d = \frac{1}{np}\sum\left(J^* - e_c J_a\right) \quad (9)$$

$$d = J^* - e_c \frac{\sum J_a}{np} \quad (10)$$

$$d = J^* - e_c \mu \quad (11)$$

$$set\ diff = e_c \mu \quad (12)$$

Eq. (11) shows the form ofocean current direction with terms such as number of jellyfish, current jellyfish at best position, attraction factor and mean location of all jellyfish are *np*, J^*, e_c and μ respectively. The *diff* in Eq. (12) indicates the difference of mean position of all jellyfish and current best position of jellyfish.

$$d = J^* - diff \quad (13)$$

Eq. (13) shows the expression to find ocean current direction. Assume that the jellyfish in the ocean is spatially distributed in all dimensions so, the distance around the mean location of all jellyfish $\pm\alpha\sigma$ has specified probability of all jellyfish in which the standard deviation of distribution is σ.

$$diff = \alpha\sigma \times rand^f \quad (14)$$

$$set\ \sigma = rand^\beta \times \mu \quad (15)$$

Eq. (15) is substituted in Eq. (14), $diff = \alpha \times rand^f \times rand^\beta \times \mu$ (16)

And it is then simplified as, $diff = \alpha \times rand \times \mu$ (17)

Based on Eq. (12), $e_c = \alpha \times rand\left(0,1\right)$ Eq. (11) is written as in Eq. (18).

$$d = J^* - \alpha \times rand \times \mu \quad (18)$$

Now, an expression for jellyfish new position is expressed in Eq. (19).

$$J_a\left(t+1\right) = J_a\left(t\right) + rand \times d \quad (19)$$

Thus, $J_a\left(t+1\right) = J_a\left(t\right) + rand \times J^* - \alpha \times rand \times \mu$ (20)

In which the distribution coefficient is $\alpha > 0$ which is related to distance of *d*.

3.1.2 Jellyfish Swarm

Jellyfish exhibits active and passive motions in swarm. The movement of jellyfish around their own positions known as active motion. Most of the jellyfish in swarm initially exhibits passive motion while time goes on the jellyfish increasingly exhibits active motion. The consequent updation on jellyfish position is shown in Eq. (21).

$$J_a(t+1) = J_a(t) + \lambda \times rand \times (ub - lb) \quad (21)$$

Here, the lower bound and upper bound of search spaces are denoted by $lb \text{ and } ub$ correspondingly and the coefficient of motion is $\lambda > 0$. Wherein, Eq. (20) and Eq. (21) are hybridized as represented in Eq. (23).

$$2J_a(t+1) = 2J_a(t) + \left(J^* - \alpha \times rand \times \mu\right) + \lambda \times rand \times (ub - lb) \quad (22)$$

$$J_a(t+1) = \frac{2J_a(t) + \left(J^* - \alpha \times rand \times \mu\right) + \lambda \times rand \times (ub - lb)}{2} \quad (23)$$

Thereby, Eq. (23) represents the proposed form of consequent position updation based on conventional expression Eq. (21).

Likewise, the passive motion of jellyfish is determined by selecting a vector from the next jellyfish randomly to the selected jellyfish is utilized to find the motion direction. The probability of movement direction is represented in Eq. (25) where, *Max C* indicates the objective function of the position *J*.

$$s = J_a(t+1) - J_a(t) \text{ where, } s = rand \times dir \quad (24)$$

$$dir = \begin{cases} J_b(t) - J_a(t) & \text{if } Max\,C(J_a) \geq f(J_b) \\ J_a(t) - J_b(t) & \text{if } Max\,C(J_a) < f(J_b) \end{cases} \quad (25)$$

Therefore Eq. (24) is given by, $J_a(t+1) = J_a(t) + s$ (26)

And the Eq. (20) and Eq. (26) are added and the added finalized expression is shown in Eq. (28).

$$2J_a(t+1) = 2J_a(t) + rand \times \left(J^* - \alpha \times rand \times \mu\right) + s \quad (27)$$

$$J_a(t+1) = \frac{2J_a(t) + rand \times \left(J^* - \alpha \times rand \times \mu\right) + s}{2} \quad (28)$$

In Eq. (28), the *rand* function is calculated using circle chaotic map [7] which is obtained by iterating the map. In which, the values of constants *g* and *h* are 0.5 and 0.2 respectively. This map generates chaotic sequence of values in the interval of [0, 1]. Thereby, the computation of *rand* function using circle chaotic map is formulated in Eq. (29).

$$rand_{J_a(t+1)} = \left\{ J_a(t) + h - \left(\frac{g}{2\pi}\right) \sin\left(2\pi J_a(t)\right) \right\} \bmod 1 \quad (29)$$

Here, the type of motion is determined by time control strategy which is not only used to control the active and passive motions yet also controls the jellyfish motion towards an ocean current.

3.1.3 Time Control Strategy

This strategy is utilized to speed up jellyfish movement between moving inside swarm and ocean current which is involved with a constant U_o and time control function *u(t)*. Here, the time control function is an arbitrary value in the interval of [0, 1] which is represented in Eq. (30). If the value of constant U_o is increased then the movement of jellyfish is toward the ocean current otherwise, it moves inside the swarm. So, the approximate value of constant U_o is not known and the time control function randomly ranges between 0 and 1. Thereby, the value of constant U_o is fixed as 0.5 which is normally ranges from 0 to 1.

$$u(t) = \left| \left(1 - \frac{t}{Max\,t} \right) \right| \times \left(2 \times rand - 1 \right) \quad (30)$$

Eq. (30) shows the mathematical model of time control mechanism where,*Max t* denotes the maximum number of iterations and it's an initial parameter and the iteration number is specified by time as *t*.

3.1.4 Population Initialization

Initially, the population of jellyfish is initialized randomly. The advantages of traditional JSO algorithm is dimmed due to low population diversity and slow convergence this can be overcome by the proposed SIJSO algorithm. And these limitations are rectified by enhanced diversity in population initialization by the use of chaotic maps. Instead of random selection, the algorithm obtains more diverse initial populations using logistic map and it also offered probability of premature convergence as lower in value. Thereby, the mathematical expression of utilized map is expressed in Eq. (31) in which the position of *a*th jellyfish logistic chaotic value J_a. The initial population of jellyfish is denoted by J_0 and its value varies between [0, 1] and the model parameter η is set to be 4.0.

$$J_a(t+1) = \eta J_a(1 - J_a), \quad 0 \le J_0 \le 1 \quad (31)$$

3.1.5 Boundary Conditions

The process of re-entering of jellyfish from outside to inside of the search space is formulated in Eq. (32).

$$\begin{cases} J'_{a,e} = \left(J_{a,e} - ub_e\right) + lb(e) \;\; if \;\; J_{a,e} > ub_e \\ J'_{a,e} = \left(J_{a,e} - lb_e\right) + ub(e) \;\; if \;\; J_{a,e} > lb_e \end{cases} \quad (32)$$

Where, the position of *a*th jellyfish in *e*th dimension is $J_{a,e}$ and the jellyfish is updated to new position as $J'_{a,e}$. The upper and lower bounds of *e*th dimension in search spaces are $ub_e \; and \; lb_e$ respectively.

3.1.6 Systematic Representation of Artificial JSO Algorithm

Exploration Phase- It describes the movement of jellyfish within the swarm.

Exploitation Phase- It describes jellyfish movement towards the ocean current.

The above explained strategy named time control strategy shifts between these two phases. Initially, the optimal positions in a region is explored while the probability of exploitation is greater than the probability of exploration. After the passage of time, the probability of exploitation exceeds than the probability of exploration which ensures that the best position of jellyfish is found inside the identified regions.

3.1.7 Algorithm 1: SIJSO Algorithm

Pseudo-code of SIJSO Algorithm			
Start			
	Find objective function		
	Initialize search space, *np* and *Max C*		
	Evaluate quantity of food at each J_a and $f\left(J_a\right)$		
	Identify the jellyfish at current position with more food, J^*		
	Initialize iteration as *t=1*		
	Repeat		
		for *i=1:np* do	
		Evaluate the time control *u(t)* by Eq. (30)	
		if $u\left(t\right) \geq 0.5$: jellyfish moves towards the ocean current	
			Identify ocean current by Eq. (18)
			Define new position of jellyfish by Eq. (20)
		else: jellyfish moves inside a swarm	
			If $rand > \left(1-u\left(t\right)\right)$: jellyfish moves in passive motions
			Define new position of jellyfish by Eq. (23)
			else: jellyfish moves in active motions
			Identify ocean current by Eq. (25)
			Define new position of jellyfish by Eq. (28)
			end if
		end if	
		Verify boundary conditions and evaluate food quantity at new position	
		Update the previous position and current position of jellyfish with more food.	
		End for *a*	
		Update iteration as $t = t + 1$	
	Until stop criterion is satisfied		
	output		
end			

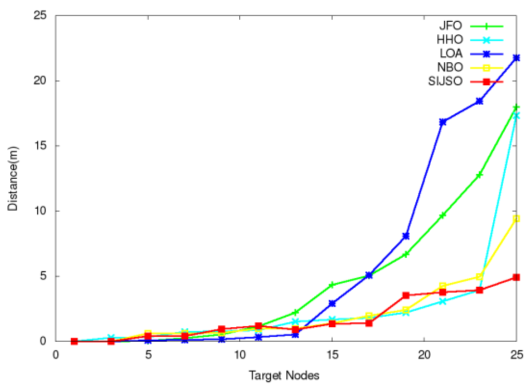
4. RESULT AND DISCUSSION

4.1 Simulation Procedure

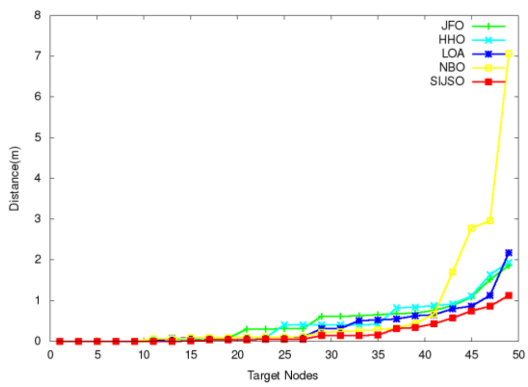
The SIJSO work for Extending coverage in WSN was implemented in NS2. Further, the SIJSO is compared with the conventional methodologies, including, JFO, HHO, LOA and NBO, respectively. Additionally, the evaluation was done in terms of distance, coverage area and so on. The analysis was made for varied sensing radius S_q (10m and 20m) while adjusting the number of target nodes from 25, 50 and 75.

4.2 Distance analysis on SIJSO and conventional methods for extending coverage in WSN

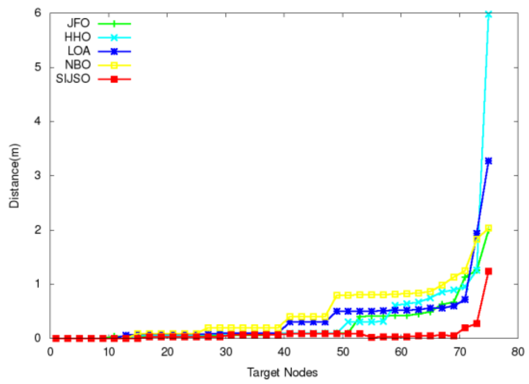
The evaluation on distance metrics for the SIJSO is contrasted with the JFO, HHO, LOA and NBO for improving the coverage in WSN. Also, it is analyzed for the sensing radius of 10m and 20m as well as the findings are shown in fig 2 and fig 3. Additionally, the analysis is done for varied number of target nodes (0-25). In order to improve the data transmission, the distance should be reduced. In a similar way, the SIJSO accomplished lesser distance rate in all the target nodes. More particularly, in the 25th target node for the 10m radius, the SIJSO obtained much lesser distance than the JFO, HHO, LOA and NBO. Furthermore, for the target node=75, the SIJSO yielded the least distance of 1.3678m for the sensing radius 20m, which is minimal over the JFO, HHO, LOA and NBO, correspondingly. Here, in the 0th target node, the SIJSO generated the least distance while as the target node improved the distance rate get increased. However, the SIJSO acquired the least distance value in all the target nodes. Therefore, the distance analysis indicates that the SIJSO outperforms the traditional schemes by improving the coverage distance with lesser distance rate.



(a)

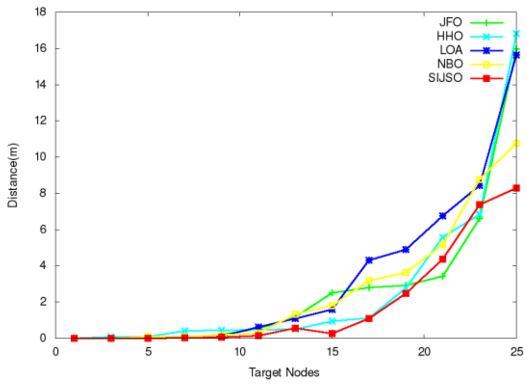


(b)

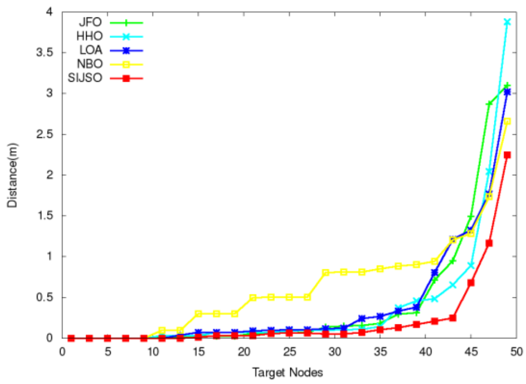


(c)

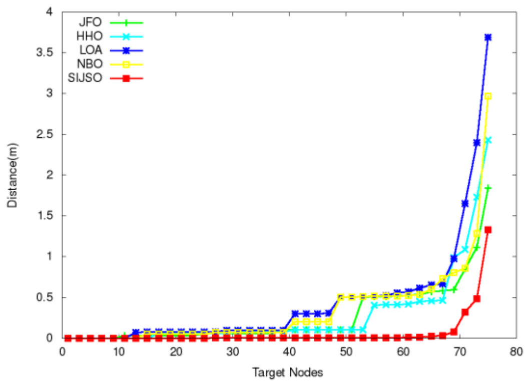
Fig 2 Assessment on distance a) 25 b) 50 and c) 75 for sensing radius 10m



(a)



(b)



(c)

Fig 3 Assessment on distance a) 25 b) 50 and c) 75 for sensing radius 20m

4.3 Statistical analysis on SIJSO and conventional methods with regard to distance for extending coverage in WSN

The statistical assessment on SIJSO over the JFO, HHO, LOA and NBO for the sensing radius 10m and 20m is illustrated in table I and table II. Further, it is evaluated by altering the target nodes (25, 50 and 75) under varied types of statistical measures. While assessing those tables, the SIJSO generated minimized distance with increased coverage in WSN. Regarding the table I, for the target node 50, the SIJSO obtained the diminished distance of 0.0584m under the median statistical measure, whereas the JFO is 0.3103m, HHO is 0.4023m, LOA is 0.1039m and NBO is 0.1086m, correspondingly. Additionally, for the sensing radius 10m, the least distance rate is attained using the SIJSO (Target Node 75) than the JFO, HHO, LOA and NBO. Hence, the SIJSO performs more successful since it consistently increase the coverage distance in WSN with reduced distance value in all the target nodes.

Table I: Statistical study on SIJSO and traditional approaches in terms of distance for sensing radius 10m

Target Node 25					
Statistical Measures	Mean	Minimum	Maximum	Median	Standard Deviation
JFO	4.2845	0.0000	17.9941	2.2158	4.9989
HHO	2.5176	0.0000	17.3366	1.5032	4.0489

LOA	5.5797	0.0000	21.7505	0.5155	7.7355
NBO	2.1082	0.0000	9.4199	0.9801	2.3972
SIJSO	1.7093	0.0000	4.9083	1.1613	1.5586
Target Node 50					
Statistical Measures	Mean	Minimum	Maximum	Median	Standard Deviation
JFO	0.5998	0.0000	7.8147	0.3103	1.1406
HHO	0.4542	0.0000	2.1409	0.4023	0.5450
LOA	0.3858	0.0000	2.4620	0.1039	0.5197
NBO	0.8316	0.0000	9.8377	0.1086	1.8572
SIJSO	0.2370	0.0000	2.0000	0.0584	0.3787
Target Node 75					
Statistical Measures	Mean	Minimum	Maximum	Median	Standard Deviation
JFO	0.2545	0.0000	2.0002	0.0600	0.3823
HHO	0.3403	0.0000	5.9804	0.0801	0.7423
LOA	0.3589	0.0000	3.2774	0.1009	0.5711
NBO	0.4664	0.0000	2.0354	0.2000	0.4812
SIJSO	0.0722	0.0000	1.2369	0.0447	0.1499

Table II: Statistical study on SIJSO and traditional approaches in terms of distance for sensing radius 20m

Target Node 25					
Statistical Measures	Mean	Minimum	Maximum	Median	Standard Deviation
JFO	2.4953	0.0000	15.9748	1.1792	3.8161
HHO	2.6482	0.0000	16.8058	0.5047	4.3997
LOA	3.0210	0.0000	15.6448	1.1008	4.0011
NBO	2.6728	0.0000	10.7637	1.3327	3.3458
SIJSO	1.6822	0.0477	8.2837	0.1852	2.6735
Target Node 50					
Statistical Measures	Mean	Minimum	Maximum	Median	Standard Deviation
JFO	0.4855	0.0000	4.1106	0.0680	0.9488
HHO	0.4750	0.0000	7.1465	0.0944	1.1825
LOA	0.4405	0.0000	3.9748	0.1033	0.7978
NBO	0.7454	0.0000	6.6611	0.5028	1.0255

SIJSO	0.2409	0.0000	2.4145	0.0532	0.5433
Target Node 75					
Statistical Measures	Mean	Minimum	Maximum	Median	Standard Deviation
JFO	0.2522	0.0000	1.8451	0.0609	0.3454
HHO	0.2698	0.0000	2.4323	0.0809	0.4627
LOA	0.4217	0.0000	3.6946	0.1007	0.6591
NBO	0.3146	0.0000	2.9735	0.0705	0.4451
SIJSO	0.0593	0.0000	1.3332	0.0058	0.2249

4.4 Analysis on coverage area of the SIJSO and the traditional methods for extending coverage in WSN

The coverage area evaluation on SIJSO is examined over the JFO, HHO, LOA and NBO for varied sensing radius (10m and 20m) while modifying the target nodes 25, 50 and 75 is exposed in table III and table IV. For the effective performance of the model, the coverage area should be maximized. Likewise, the SIJSO generated the highest coverage area in all the target nodes. In particular, at the sensing radius 10m, the SIJSO acquired the coverage area of 0.8734(Target Node=75), meanwhile the JFO, HHO, LOA and NBO offered the least coverage area. Simultaneously, analyzing the target node 25, the SIJSO yielded the least distance rate for the sensing radius 20m. Thus, the SIJSO method has emphasized its improvement for increasing the coverage in WSN with higher coverage area in all the target nodes.

Table III: Analysis on coverage area for SIJSO and conventional methods for 10m sensing radius

Algorithm	Coverage Area for Target Node 25	Coverage Area for Target Node 50	Coverage Area for Target Node 75
JFO	0.8609	0.8537	0.8597
HHO	0.8713	0.8556	0.8543
LOA	0.8626	0.8467	0.8492
NBO	0.8710	0.8666	0.8513
SIJSO	0.8772	0.8752	0.8734

Table IV: Analysis on coverage area for SIJSO and conventional methods for 20m sensing radius

Algorithm	Coverage Area for Target Node 25	Coverage Area for Target Node 50	Coverage Area for Target Node 75
JFO	0.8580	0.8572	0.8625
HHO	0.8502	0.8542	0.8521
LOA	0.8741	0.8572	0.8659
NBO	0.8681	0.8591	0.8563
SIJSO	0.8904	0.8615	0.8712

5. Conclusion

This research work was intended to propose an efficient methodology for expanding the coverage in networks. Thereby, this work was proposed with a self-improved optimization algorithm called SIJSO to maintain an optimal positioning of sensor nodes in appropriate positions. This proposed approach was particularly implemented for WSNs to enhance its network coverage. Its significance on network coverage enhancement was simulated in NS2. Also, the analysis is carried out in terms of distance, coverage area and so on. Furthermore, for the target node=75, the SIJSO yielded the least distance of 1.3678m for the sensing radius 20m, which is minimal over the JFO, HHO, LOA and NBO, correspondingly.

REFERENCE

[1] Qiang Liu, "Coverage Reliability Evaluation of Wireless Sensor Network Considering Common Cause Failures Based on D–S Evidence Theory," in IEEE Transactions on Reliability, vol. 70, no. 1, pp. 331-345, March 2021, doi: 10.1109/TR.2020.2999576.

[2] Xinmiao Lu, Yanwen Su, Qiong Wu, Yuhan Wei and Jiaxu Wang, "An improved coverage gap fixing method for heterogenous wireless sensor network based on Voronoi polygons". Alexandria Engineering Journal, Vol. 60, pp.4307–4313, 2021.

[3] Li Li and Hongbin Chen, "UAV Enhanced Target-Barrier Coverage Algorithm for Wireless Sensor Networks Based on Reinforcement Learning". Sensors, Vol. 22, 6381, 2022. https://doi.org/10.3390/s22176381

[4] Pingzhang Gou, Baoyong Guo, Miao Guo and Shun Mao, "VKECE-3D: Energy-Efficient Coverage Enhancement in Three-Dimensional Heterogeneous Wireless Sensor Networks Based on 3D-Voronoi and K-Means Algorithm". Sensors, Vol. 23, 573, 2023. https://doi.org/10.3390/s23020573

[5] Suparna Chakraborty, Neeraj Kumar Goyal and Sieteng Soh, "On Area Coverage Reliability of Mobile Wireless Sensor Networks With Multistate Nodes". IEEE SENSORS JOURNAL, VOL. 20, NO. 9, MAY 1, 2020.

[6] Jui-Sheng Chou and Dinh-Nhat Truong, "A novel metaheuristic optimizer inspired by behavior of jellyfish in ocean". Applied Mathematics and Computation, Vol. 389, 2020.

[7] Hui Lu, Xiaoteng Wang, Zongming Fei and Meikang Qiu, "The Effects of Using Chaotic Map on Improving the Performance of Multiobjective Evolutionary Algorithms". Mathematical Problems in Engineering, Vol. 2014, Article ID 924652, http://dx.doi.org/10.1155/2014/924652

[8] Haifeng Ling,1 Tao Zhu , Weixiong He, Hongchuan Luo, Qing Wang,1 and Yi Jiang, Coverage Optimization of Sensors under Multiple Constraints Using the Improved PSO Algorithm, Hindawi Mathematical Problems in Engineering, Vol. 2020, Article ID 8820907, 10 pages, https://doi.org/10.1155/2020/8820907

[9] Zhaoming Miao Xian feng Yuan Fengyu ZhouKe Chen, “Grey wolf optimizer with an enhanced hierarchy and its application to the wireless sensor network coverage optimization problem”. Applied Soft Computing, Vol. 96, Article 106602, November 2020.

[10] Daifeng Zhang Jiliang Zhang, “Multi-species evolutionary algorithm for wireless visual sensor networks coverage optimization with changeable field of views”. Applied Soft Computing, Vol. 96, Article 106680, November 2020.

[11] S. Balaji M. Anitha D. Rekha D. Arivudainambi, “Energy efficient target coverage for a wireless sensor network”. Measurement, Vol. 165, Article 108167, 10 July 2020.

[12] Huynh Thi Thanh Binh Nguyen Thi Hanh La Van Quan Nilanjan Dey, "Metaheuristics for maximization of obstacles constrained area coverage in heterogeneous wireless sensor networks", Applied Soft Computing, January 2020. Volume 86 Article 105939.

[13] Aparajita ChowdhuryDebashis De, “FIS-RGSO: Dynamic Fuzzy Inference System Based Reverse Glowworm Swarm Optimization of energy and coverage in green mobile wireless sensor networks”, Computer Communications, Vol. 163, pp. 12 - 34, 2020.

[14] Faten Hajjej, Monia Hamdi, Ridha Ejbali, Mourad Zaied, "A distributed coverage hole recovery approach based on reinforcement learning for Wireless Sensor Networks", Ad Hoc Networks, Vol. 101, 15 April 2020, Article 102082.

[15] Pingzhang Gou, Gang Mao, Fen Zhang, Xiangdong Jia, "Reconstruction of coverage hole model and cooperative repair optimization algorithm in heterogeneous wireless sensor networks", Computer Communications, vol. 153, pp. 614 - 625, 1 March 2020.

Author-01 (MAIN AUTHOR)

Swati is an Asst.Professor in the department of Artificial Intelligence & Machine Learning at Sharnbasva University, Kalaburagi. Currently pursuing research in department of Computer Science & Engineering at Sharnbasva University, Kalaburagi. She received Bachelor's and Master's degree in Computer Science & Engineering from VTU and JNTU Hyderabad respectively. Under the guidance of Dr. Sujata V. Mallapur, Professor Sharnbasva University, Kalaburagi.

Email: swatishivakumarkagi@gmail.com

Author-02

Sujata V. Mallapur Currently working as Professor & Research Dean in the department of Artificial Intelligence & Machine Learning, Sharnbasva University, Kalaburagi. She received BE in Information Science & Engineering and M.Tech. in Computer Science & Engineering degrees and Ph. D in Electronics & Communication Engineering from Poojya Doddappa College of Engineering, Gulbarga, Karnataka, India under Visvesvaraya Technological University, Belagavi, Karnataka, India in 2004, 2008 and 2018 respectively. She is a life Member of Indian Society for Technical Education (ISTE), India, Senior member of Institute of Electrical and Electronics Engineers (IEEE) and Fellow of Institute of Electronics and Telecommunication Engineers (IETE), India. She has published more than 15 research papers in various national and international journals and conferences. She has guided many BE and M.Tech. Projects, and guiding more than 5 Ph. D students. Her research includes Computer networks, Wireless Networks, Mobile Ad Hoc Networks (MANETs), Vehicular Ad Hoc Networks (VANETs) and Wireless Sensor Networks (WSNs).

Email: sujatavmallapur@gmail.com