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A Multi-Objective Sensor Deployment using BAT Algorithm to Improve Coverage, Lifetime and Energy Consumption in Wireless Sensor Networks

Shaik Imam Saheb[1]* **Khaleel Ur Rahman Khan[2]** **C. Shoba Bindu[1]**

[1]*Department of Computer Science Engineering, Jawaharlal Nehru Technological University Anantapur, Ananthapuramu, Andhra Pradesh, India*
[2] *Department of Computer Science Engineering, ACE Engineering College, Hyderabad, India*
* Corresponding author's Email: shaikimamsa@gmail.com

Abstract: In the dense sensing environment, deployment of multiple sensor nodes is included in the WSNs. Based on the sensor deployment scheme, the WSNs' effectiveness has been provided up to the extent that relied on the network coverage. Some of the major objectives relevant to the sensor nodes' deployment that are required to be satisfied are the network connectivity, number of deployed sensors, lifetime, overall consumption of energy, and area coverage. The deployment of sensor nodes has been carried out based on a constrained problem of multi-objective (MO) that includes the objective of determining the sensor node arrangement for improving the coverage area, decreasing the energy consumption, improving the network lifetime, and network connectivity between SINK and node for accurate data transmission. Based on Bat Algorithm (BA), the node deployment with the proposed technique is discussed for improving the sensor nodes' coverage rate. However, each bat is determined the solution based on the sensor nodes' deployment. Further, the bat algorithm (BA) has been improved to enhance the sensor nodes' coverage rate. According to the value of fitness function, the bat movement is chosen in the enhanced bat algorithm. The node deployment using the improved bat algorithm have been compared with RSSI based node deployment method, called as hybrid DP-HOP and particle swarm optimization approach CPSO. Compared with Hybrid DP-Hop & CPSO techniques, the proposed node deployment technique achieved 60% throughput gain, improves PDR by 30% and reduce the end to end delay by 40% and optimized energy consumption.

Keywords: WSN, Maximum network lifetime, Minimal energy consumption, Maximum coverage, BAT algorithm, Multi-objective optimization.

1. Introduction

The distribution of sensor nodes has been performed across the geographical area in a WSN [1]. The level of intelligence and capability of wireless communication has been included for signal processing and networking. The major problem of the sensor node designing is to be monitored the nodes [2]. The limited capabilities like communication, storage, and low processing have been included in the sensor nodes. The consumed energy should be lower while the deployed nodes operate with a certain time interval [3]. A severe constraint has been imposed by the node batteries' replacing or recharging impossibilities, specifically in the deployed networks: A limited lifetime has been included for each node in the network that can't be extended. The area monitoring is concerned, which is the major objective of the sensor node deployment. By developing the detection of events uniformly or differentiated event detection, the area monitoring may be included, in which the event appearance probability in the area is varied in terms of geographical path and time. The transmission of collected data can be performed through the other nodes to SINK from an individual sensor node that maintains the network connectivity among sensor nodes. The challenging issue of satisfying all such objectives together in the sensor nodes' deployment [4].

All WSNs have been concerned about energy consumption as limited battery life is included for all nodes as the nodes integrate with battery as they can't replace after deployment [5]. The higher data processing is required for the nodes that are nearer to the SINK and the network lifetime shortening is caused because of expiry power of battery in the nodes. The sensor node’s deployment is relied on the application, sensors type, and the environment, in which the network will operate. It’s a pre-determined or random sensor nodes’ deployment can be involved [6]. Generally, the network involves the nodes that are deployed randomly within the inaccessible terrain. In the indoor applications, the locations of nodes have been specified based on the predetermined manner in the nodes’ deployment.

In WSNs, the significant issue is the sensor nodes’ coverage that has shown the impact on the wireless network’s performance [7-10]. The network coverage problems can be caused by the sensor nodes’ initial arbitrary positioning in real-time scenarios [11]. For enhancing the sensor nodes’ coverage rate, their position is optimized [12-15].

Different optimization methods have been proposed by various researchers for increasing the sensor nodes’ coverage rate of WSNs. In [16], node deployment was proposed by using particle swarm optimization for energy consumption reduction and nodes’ coverage enhancement. Kulkarni et al., [17] were introduced the Bacterial Foraging Algorithm (BFA), where the sensor nodes were deployed. In [18], Glowworm swarm optimization was utilized for sensor nodes’ positioning, where the coverage maximizes with a few nodes’ activities that optimizes the energy consumption. Zhang et al., [19] were modified the artificial bee colony (ABC) algorithm with some constraints for improving the convergence speed. In [20], a variable-length genetic algorithm has been proposed to reduce the deployment cost for the monitoring field of nodes.

The deployment of sensor nodes has been performed in the research work in a given area for all of the aforementioned objectives, including (i) maximizing the coverage area of nodes that detect the event in the interest region and data sent to the SINK; (ii) reducing all network nodes’ energy consumption; (iii) improving the network lifetime; (iv) reducing the cost and deployment payload based on sensor nodes; (v) the network connectivity enhancement in the configuration of sensor network that allows communication of each node with the sink node.

Based on the decentralized and self-organized collective behaviour of systems, swarm intelligence is focused that focuses on interacting with the simple local agents and with their environment. It is an artificial algorithm type. A global pattern is often caused to emerge often by following some simple rules by the agents with local interaction with other agents even though the centralized control is not there for dictating the agents’ behaviour. In nature, the systems like glow-worm swarm, birds flocking, ant colonies, etc. can be found. The pheromones update values and state rules changes is followed in the ant colony optimization that simulates the individual agent with ant characteristics for solving the NP-hardness problem. By using the particle swarm optimization, the solution is determined for the optimization issue in the search space and the social behaviour is predicted while objectives presence. By using the bats’ echolocation behaviour, the new meta-heuristic technique known as bat algorithm (BA) was proposed. BA has been improved by taking the benefit from previous algorithms and other features that inspired due to the micro bats’ with the fantastic behaviour of echolocation. When compared to the other previous algorithms, BA is provided with better results in efficiency and accuracy. A sensor deployment approach is presented by using the bat algorithm (BA) for improving the network coverage after deploying the sensor nodes.

The foraging strategies or techniques have been used to modify the original bat algorithm. The movement of bat is chosen by the fitness function of the modified bat algorithm. The bat movement type is swimming when it is moved towards the fitness function with optimum value. The original bat algorithm supports only swimming type movement (single direction), but both tumbling and swimming bat moves in opposite directions from the previous direction have been supported in the modified bat algorithm. Once the bat reaches to the direction of its target like increasing or decreasing fitness, this kind of bat movement is stopped. The negative results may cause in case of not existing the opposite direction movements and not able to explore all directions across the solution space.

Contribution of the paper:

- The existing bat algorithm (BA) is improved in this work and the bat movement is chosen according to the value of fitness function.
- In the earlier step, the type of bat movement is in the similar direction if it is moving towards the fitness function’s optimum value in IBA. Otherwise, the different direction is followed by bat absolutely from the previous one.
- Due to this, the bats have been explored all directions in the space of solution and find better optimal solutions.

The coverage rate for sensor nodes has been improved using this approach during the initial deployment that will improve the overall connectivity of a network. The modified bat algorithm makes the selection of bat movement as per the value of fitness function. The bat moves in the same direction of the previous step when it moves towards the fitness function's fitness value. Otherwise, the different direction is followed by the bat from the earlier one. So that BATs can explore all the area in the search space and an optimal solution can be achieved.

Rest of this paper is organized as follows: Section 2 reviews previous work. Section 3 presents the system model and proposed algorithm. Section 4 evaluates simulation results. Section 5 concludes the paper with future works.

2. Literature review

For addressing the problem of sensor deployment in WSNs, different techniques have been proposed. In this section, a few related techniques have been presented in this paper.

In [21], the authors have determined the solution for the K-coverage problem of WSNs based on a genetic algorithm (GA) while focusing on the network's energy consumption. Different factors like the consumed energy, positions of targets, and each sensor node's coverage range are considered in this algorithm. In the GA fitness function, the network lifetime has not been considered that means it doesn't achieve the prolonged lifetime hence the network may die very quickly.

In [22], the authors have proposed a new technique that defines the virtual nodes that can be merged, moved, recombined, and exploding for determination of a solution to the simple coverage issue that occured in the WSNs. This method reduces the number of actual sensors, i.e. the virtual sensors to maintain the full network coverage. But the end results were not satisfied enough in terms of complete coverage and network lifetime.

In [23], the authors have been proposed the mobile sink based coverage optimization and link stability routing (MSCOLER) technique for prevention of transmission failures and recovery of network coverage. The modeling of coverage problem has been carried out as the non-constrained optimization to maximize the coverage. But the failure of MS leads to serious data loss and no fault tolerance is provided with this method.

In [24], the authors have introduced the bee algorithm that optimizes the network coverage. The MATLAB software was used for simulation of proposed method and made the comparison with the genetic algorithms. The optimum coverage percentage has resulted from the bee algorithm than the genetic algorithm.

In [25], the authors have addressed the mobility nodes' new position to increase the coverage area and determine the coverage hole in the monitoring area that doesn't cover by the sensing network. Based on the simulation results, the recovery of coverage hole is showed by the mobile nodes appropriately while the mobility recovers the coverage holes. After mobility, the number of coverage holes is more when the lower or equal number of nodes up to 200 are there. And the coverage holes cause serious data loss and increase the overhead.

In [26], the authors have presented a mathematical model for optimizing the active density of network sensor nodes and the concentric hexagonal tessellations using the coverage distribution area. To overcome the k-coverage problem, the optimized solution is generated and achieved the expanded network lifetime. Based on the mathematical analysis, the technique's efficacy and superiority have been validated using MATLAB software.

In [27], the authors have proposed the improved version of DV-Hop localization technique, known as Hybrid DV-Hop algorithm. The sensor nodes' localization is performed progressively using the proposed technique to be allowed the earlier localized sensor nodes have been acted as anchors and other remaining nodes are localized. The proposed algorithm performance has been compared with the selective 3-Anchor DV-hop algorithm and RSSI auxiliary ranging with the performance evaluation. The simulation results prove that the proposed algorithm hybrid DV-Hop outperforms in terms of localization accuracy with 95 %, 90 %, and 70 % than the original DV-Hop, Selective 3-Anchor, and the RSSI DV-Hop algorithms, respectively. But, the proposed algorithm lacks in achieving the improved localization accuracy and distance estimation accuracy for reduced transmission range. It needs further developments to become the optimized choice for localization accuracy for WSNs.

In [28], the authors have used the PSO algorithm with improved versions in the determination of solutions for deployment issues. They are the cooperative PSO and cooperative PSO based fuzzy logic. The proposed algorithm can able to resolve the issue of network coverage than the other existing algorithms. But the author did not consider the local optima issue that exists in PSO generally, hence this method tends to fail in some of the applications after few rounds of communications.

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Problem formulation

The monitoring area is categorized into the set of points, known as demand points for modelling the WSN coverage. The sensing is required for demand points. The 'n' number of small square tiles are categorized from overall sensing area. Each square tile's centre considers as the demand point. A definite sensing radius of Rsense has been included in each node and the demand points are required to be covered within the circle of radius by that sensor node to overcome the coverage issue in WSNs. However, the connectivity defines as the one path should be there between sink and sensor node for the least case. If the lesser distance is there Rcomm (range or radius of communication) between sensor nodes, they have been referred to be connected. At the sensor node, the consumer energy is categorized into three parts, such as: (i) transmission energy: The energy is required to transmit the data from sensor node to SINK node through a path; (ii) reception energy: It is consumed by using a number of nodes that would be played a key role in receiving the data that transmitted to the SINK node; (iii) maintenance energy: the nodes are maintained in the active state. A particular initial energy has contained at each node. The node's consumed energy is used to measure its working time and computes the network lifetime. WSN's coverage model is showed in the below section.

3. System model

3.1 Coverage model for WSN

In the WSNs, 'm' sensor nodes are deployed in 2D region while they are represented as N = {N1, N2,…Nm}. The position of ith node defines as the Ni = (xi,yi), where, i = (1,2…m). Based on Eq. (1), the ith sensor node's Euclidean distance can be determined using the grid point G(x,y):

$$d = \sqrt{(x - x_i)^2 + (y - y_i)^2} \tag{1}$$

Where, x and y indicate the grid point G coordinates; xi and yi represent the coordinates of sensor node Ni.

A binary detection model is followed in our work and coverage of the sensor node N_i at grid point G is defined as follows in Eq. (2):

$$CV_{xy}(N_i) = \begin{cases} 1, \ d \leq r \\ 0, \ otherwise \end{cases} \tag{2}$$

Where, d refers to the Euclidean distance between ith sensor node and grid point while r is the sensing radius of a node.

The coverage optimization problem has a major objective of providing a sufficient coverage rate according to the lower number of nodes. The performance of a network is determined by using the coverage rate CVR is used that can be estimated using below Eq. (3):

$$CVR = \frac{GP_{sum}}{PQ} \tag{3}$$

The partitioning of 2D area is done into P*Q grid points and GPsum is represented the grid points summation that covered by the sensor nodes.

3.2 Bat algorithm

In 2010, Xin She Yang [29] has introduced the bat algorithm that was inspired by microbats in nature. The echolocation was employed in the microbats to differentiate and locate the prey, determine the batteries, and detect the locations of roosting. The higher frequency ultrasonic pulses emission is included in the echolocation and the reflected echo is heard from the surrounding surfaces that are bouncing back. By relying on the bat species and the bat surroundings, the emitted pulses are of varying frequencies. To detect the particular prey's location, the bats are enabled while reflecting the echo with different time delays and sound levels and capturing it.

X bats' with initial population is evaluated and the global solution has been found out in the nd dimensional hyperspace. Here, the optimal parameters of n are estimated. A bat i will locate at xid in the given dimension of the hyperspace d, where $1 \leq d \leq nd$ and $1 \leq i \leq B$. If an objective function $g(x_1; x_2; ... x_{nd})$ is used, the individual bats are evaluated.

During the optimization, each bat's position xid and velocity vid have been updated for each bat. The Eqs. (4), (5), and (6) are used to compute the velocities v_i^t and positions x_i^t:

$$f_i = \beta(f_{max} - f_{min}) + f_{min}; \ \beta \in [0,1] \tag{4}$$

$$v_i^t = f_i\left(x_i^t - x^*\right) + v_i^{t-1} \tag{5}$$

$$x_i^t = v_i^t + x_i^{t+1} \tag{6}$$

Where β refers to the uniformly distributed random vector. To choose the global best solution x^*, all locations of the bat are compared. A change in either λ_i or f_i changes the bat velocity as $v_i = \lambda_i * f_i$, where λ_i refers to the ultrasonic wave's

Table 1. Notation used in proposed algorithm

f_{max}	Maximum frequency
f_{min}	Minimum frequency
x_i^t	Position of BATS at time 't'
v_i^t	Velocity of BATS at time 't'
L	BAT loudness
X_{init}	Initial X position
Y_{init}	Initial Y position
U_b	Upper bound value
L_b	Lower bound value
d	Distance between nodes
α_i	Random number between [-1,1]

wavelength with frequency fi. The random frequency $f_i \in [f_{max}, f_{min}]$ is assigned to each bat initially. The best solution (x^*) has been generated by a new local solution using the below Eq. (7) based on the random walk:

$$x_{new} = x_{old} + \alpha L; \quad \alpha \in [-1,1] \tag{7}$$

Where L represents the bat loudness and α indicates the random number. As the bats reached zero in on the prey, the loudness (Li) reduces and the pulse rate (ri) increases. Table 1 shows the notations used in proposed algorithm.

3.3 Proposed IBA based node deployment

To improve the accuracy of BA algorithm, it uses the existing methods in addition to the other features that are inspired by the echolocation behaviour. The improved BA algorithm outperforms the earlier techniques in terms of efficiency and accuracy. The major issue of an algorithm is the lower success rate due to that it can't able to explore all directions of the search space. So, an existing BA must be modified to overcome this issue.

A modified bat algorithm is developed using foraging strategies. The fitness function determines the bat movement in the modified technique. The bat movement type is swimming when its movement is towards the fitness function's optimal level. The original bats algorithm only considers the swimming type movements' observation in one direction while the modified algorithm takes into account both swimming and tumbling movement, where the bat is moving in an opposite direction from the previous bat direction. Bats continue making this type of movement until they go towards their target, i.e. reducing or increasing the fitness value. If an opposite direction movement is not there, all directions couldn't be explored by a bat in the solution space that may lead to the negative results.

In WSNs, the deployment of nodes is a crucial issue. For improving the sensor nodes' coverage rate, the BA has been implemented to overcome the problem. To determine the target for the monitoring area, the sensor nodes or bats are generated initially based on some random velocities and positions. The positions of a node and the Euclidean distance between coordinates of grid points have been evaluated. The average distance is computed while storing the coordinates and minimum distance. Based on the proposed modified fitness function in IBA, the fitness function is computed and updated the nodes' position, frequency, and velocity. The above process is repeated until the maximum iterations are reached if the position is updated.

Improved bat algorithm IBA

The fitness function value is decided by the bat movement selection and modified by the original bat algorithm. The movement type of bat is in a similar direction of the previous step when a bat is moving towards the fitness function's optimum value. Or else, the bat has followed the different direction from previous one. The improved behaviour of the bat is represented as in Eq. (8):

$$x_i^t = x_i^{t-1} + v_i^t \frac{\alpha_i}{\sqrt{\alpha_i^t * \alpha_i}} \tag{8}$$

Where α_i refers to the generated random number in the range [-1,1] and v_i^t indicates the velocity at time t.

In the original bat algorithm, the same direction of the type of bat movement is only possible but in an improved bat, the same and opposite direction movement is also possible for individual bats. Until the bat is reached to the target indirect, the bat's movement is continued. The bat movement is in the similar direction as the earlier step if the movement of the bat is to the fitness function's optimum value. The different direction of the previous one has been taken by the bat otherwise.

Based on IBA, the node deployment is included in different steps, including:

Step 1:- Initialize the bat population, loudness L, pulse rate r, velocity v, & pulse frequency f. The initial positions of the bats are described as follows in Eqs. (9) and (10):

$$X_{init} = L_b + (U_b - L_b)\, rand \tag{9}$$

$$Y_{init} = L_b + (U_b - L_b)\, rand \tag{10}$$

Here, L_b & U_b are upper and lower bound values of the network area; $rand$ is the random number.

Step 2:- In the bat population, the individual bats' fitness has been evaluated based on the fitness function. Eq. (11) is used to compute the distance between sensor nodes:

$$d = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2} \tag{11}$$

Here, (x & y) are the coordinates of the bats i & j respectively.

Step 3:- update the location and velocities of the bats where the positions x_i^t and velocities v_i^t, at time t, are computed as per Eqs. (4-6) and a new solution is generated using the Eq. (8).

Step 4:- sort the bats based on the obtained fitness values of individual bats.

Step 5:- check whether the pulse rate r_i is smaller than the random vector then search and choose the best one from the created solutions and a local solution is required to generate around the best-chosen solutions based on Eq. (7).

Step 6:- if the pulse rate r_i is smaller than the random vector then a new solution is generated according to the random flying using Eq. (7).

Step 7:- if the generated random vector is lesser than the loudness L of the bat and higher than the global best solution x^*, then generate new solutions.

Step 8:- The new solutions will be used for banks' ranking and the current best value of x^* is chosen.

Psedocode for the proposed improved bat algorithm

Objective function $f(x), x = (x_1, x_2, \dots x_d)$
Initialize the bat population $x_i = (i = 1,2,3, \dots n) and\ v_i$
Define Pulse frequency f_i at x_i
Initialize the rates r_i and the loudness L_i
While ($t < Max\ number\ of\ iterations$)
Generate new solution & update location, velocity according to Eq. (1-3).
Generate new solutions as per Eq (5)
If ($rand > r_i$)
Select a solution among the best solutions
Generate a local solution around the selected best solution
End if
Generate a new solution by flying randomly
If ($rand < L_i$) & $\{f(x) < f(x^*)\}$
Accept the new solutions
Increase r_i and reduce L_i
End if
Rank the bats and find the current best x^*
End while

4. Experimental results and discussion

The experimental settings and the simulation results have been demonstrated. In the experimental section, the proposed algorithm simulation is carried out using the NS-2 simulator tool and the algorithm's performance has been validated through the parameter's adjustment and comparison with the other algorithms. The network area is fixed as 1000x600. The network size is varied from 25 to 100 nodes. The sensor nodes are assigned with 100j initial energy. The SINK position is fixed at (500,300) in all the simulation experiments. CBR is configured as a traffic type in the network. The simulation trials have been performed for the above-listed parameters using IBA for validating the node deployment's efficiency. The proposed IBA based node deployment method's performance is compared with the CPSO [28], Hybrid DP-Hop [27], MSCOLER [23], and KCGA [21]. Table 2 shows the used simulation parameters for IBA. The comparison analysis of proposed method with existing methods are listed below Tables 3-7.

End-to-end delay defines as the duration or time period is taken for data packets' transmission from the source to destination nodes over the network. The proposed technique with end-to-end delay results have been evaluated as mentioned in the above-listed table. An efficient node placement strategy used in the proposed method determines the optimal positions for the sensor nodes which improves the coverage between the nodes. With the improved connectivity, the sensor nodes can connect with the neighbor nodes with minimum time delay which results in an overall reduction in end-to-end delay. The minimum average delay was resulted as 0.209 ms in the network while the previous methods yield a high delay up to 0.260ms compared to the proposed method. Fig. 1 shows the performance delay on network.

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Table 2. Simulation experimental parameters

Parameter	**Value**
Network area	1000m x 600m
Number of sensor nodes	25,50,75,100
Routing protocol	AODV
Initial energy	100 j
Simulation time	100 s
SINK position	(500,300) (fixed)
Traffic type	CBR
Packet size	512
Transmission agent	UDP

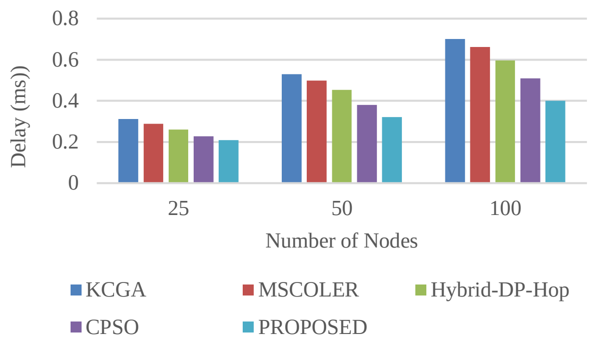

Figure. 1 End to end delay

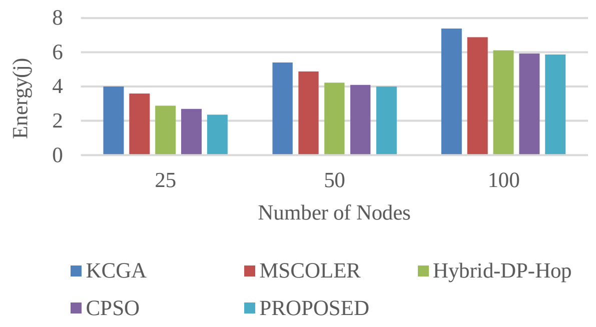

Figure. 2 Energy consumption

Table 3. Comparison analysis of proposed with existing methods for delay

NODE	**PROPOSED**	**CPSO [28]**	**Hybrid DP-Hop [27]**	**MSCOLER [23]**	**KCGA [21]**
25	0.209	0.228	0.260	0.289	0.312
50	0.321	0.380	0.453	0.498	0.530
100	0.401	0.509	0.596	0.662	0.701

Table 4. Comparison analysis of proposed with existing methods for energy levels

NODE	**PROPOSED**	**CPSO [28]**	**Hybrid DP-Hop [27]**	**MSCOLER [23]**	**KCGA [21]**
25	2.36	2.703	2.895	3.59	4.01
50	4.01	4.105	4.234	4.89	5.41
100	5.87	5.925	6.110	6.88	7.39

The deployment of sensor nodes is performed based on their initial energies to carry out the network activities as the energy depletes for each network activity. In every network, the optimization of energy should be concerned with achieving prolonged network activity. The unnecessary energy consumption is reduced by deploying the nodes efficiently and the improved coverage based on enhanced BAT. In the proposed technique, the average energy consumption rate was recorded as 2.5j. Fig. 2 represent the overall energy consumption of network.

The route maintenance and route discovery are being in part of broadcasting the control packets. During runtime, the control packet has been broadcasting over the network. The overhead is minimized by the fewer control packets. In the improved BAT algorithm, the improved coverage reduces the frequent link failure possibilities due to

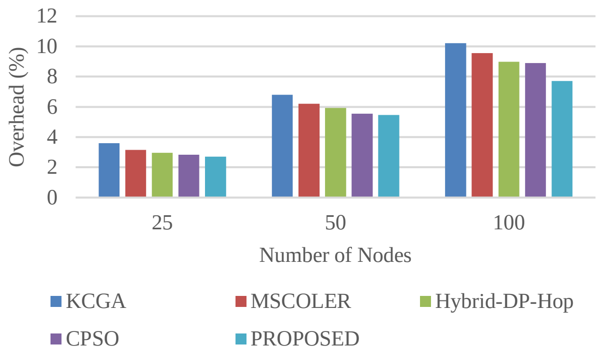

Figure. 3 Routing overhead

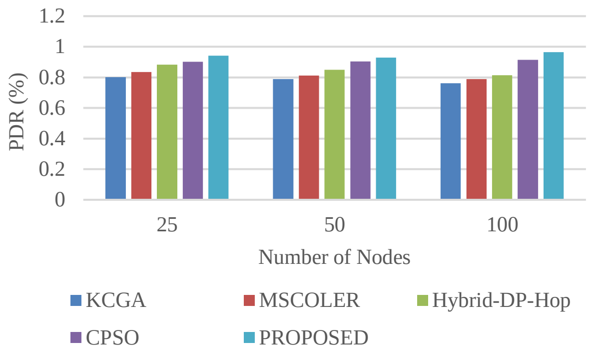

Figure. 4 Packet delivery ratio

Table 5. Comparison analysis of proposed method with existing methods for routing overhead

NODE	PROPOSED	CPSO [28]	Hybrid DP-Hop [27]	MSCOLER [23]	KCGA [21]
25	2.71	2.84	2.97	3.15	3.59
50	5.46	5.54	5.94	6.21	6.80
100	7.72	8.89	8.99	9.56	10.21

Table 6. Comparison analysis of proposed method with existing methods for PDR

NODE	PROPOSED	CPSO [28]	Hybrid DP-Hop [27]	MSCOLER [23]	KCGA [21]
25	0.9426	0.9026	0.8835	0.8347	0.8012
50	0.9281	0.9048	0.8496	0.8128	0.7884
100	0.9653	0.9137	0.8138	0.7891	0.7611

Table 7. Comparison analysis of proposed method with existing methods for throughput

NODE	PROPOSED	CPSO [28]	Hybrid DP-Hop [27]	MSCOLER [23]	KCGA [21]
25	232.26	218.42	205.06	196.25	183.20
50	307.50	272.96	230.91	201.29	194.87
100	268.10	240.12	208.13	215.67	203.47

the efficient strategy of node placement in the network. Because of the increased stability of network links, the broadcasting of the control packet was kept to a minimum. By comparing with the earlier techniques, the lower average overhead of 0.3 was resulted using the proposed technique. Fig. 3 shows the routing overhead of network.

PDR can be demonstrated as the ratio between the received and the sent packets. The placement of sensor nodes at the optimal position determined by the improved BAT and the coverage improvement between the nodes due to the optimal placement helps to forward the data for the target node successfully. The proposed method achieved a maximum PDR of 0.965 % whereas the existing methods maintained the average PDR rate of 0.92 which is a comparatively low PDR rate. The performance on delivery ratio shows in Fig. 4.

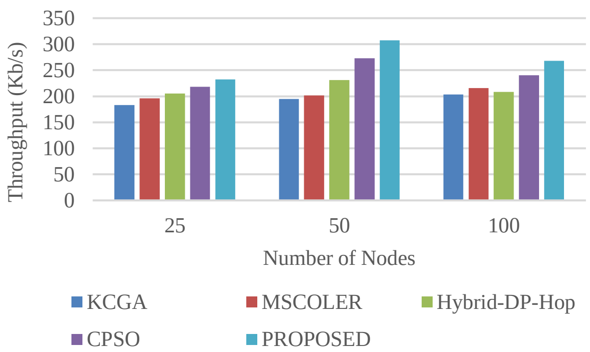

Figure. 5 Throughput of network

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The total number of data units' measurements is defined as the throughput for a given time. The proposed technique of IBAT determines the optimal placement of sensor nodes at a particular position and the data aggregation improves by the increased coverage among sensor nodes. A higher throughput rate has been provided with the implementation of proposed method compared to the existing methods as shown in the above table. The average throughput rates up to 270kbps has been maintained by the proposed technique while the lower throughput rate is maintained at the existing methods than the proposed method. Fig. 5 represents the Network performance.

On the whole, the main drawback that leads to low performance of the compared CPSO & hybrid DP-Hop methods is that CPSO utilizes the traditional particle swarm optimization method (PSO) as their base method to solve the node deployment problem. However the main challenge in using PSO is controlling PSO to fall in local optima. After some point of time, the CPSO failed to explore the search space fully due to local optima. In hybrid DP-Hop, it makes use of a network topology to determine the nodes' positions. Primarily, the algorithm is determine the hop-distance between nodes' pairs through the shortest paths' discovery between them. In addition to these paths, the average distance per hop can be computed using the nodes as their location coordinates have been pre-specified. In order to estimate the distance from each anchor node of a network, the average distance per hop can be used by sensor nodes that realize their hop-distance from anchors. But, this technique fails in different aspects because of the lower positioning accuracy.

5. Conclusion

In this paper, the improved bat algorithm (IBA) based strategy of node deployment proposes for improving the multi-objective issues, such as: (i) improving the network lifetime; (ii) achieving the network connectivity in the deployed one; (iii) improving the coverage area by the sensor nodes; (iv) reducing the consumption of energy among all nodes, and (v) reduce the cost. Based on the fitness function of a proposed algorithm, the original bat algorithm was modified and movement for a bat is chosen. The improved bat algorithm has been evaluated in terms of node deployment and compared with the other earlier methods. However, the proposed technique is outperformed the previous techniques in terms of improved coverage rate. The proposed node deployment strategy improves the energy consumption by 30 % and reducing the overhead of the network by 40 % and maintain the throughput and PDR rate for 20 % respectively.

Further research will focus on comparison of proposed algorithm's performance with other existing popular technique in the localization of WSNs. The algorithm that hybrids with another algorithm may be effective equally.

Conflicts of interest

The authors declare no conflict of interest

Author contributions

Shaik Imam Saheb, Research Scholar carried out the work to conceptualize, design and implement the Improvement of the Optimal Placement of nodes in WSN using BAT algorithm (IBAT) techniques. This method has been compared with existing methods and the results were analysed and found effective for the node placement. The simulation was carried using NS2 and based on the results the manuscript was written. The entire work has been done under the Supervision of Dr Khaleel Ur Rahman Khan and Dr C. Shoba Bindu.

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