A novel competitive cuckoo search algorithm for node placement in wireless sensor networks

Monica Shivaji Gunjal[1,2], Pramodkumar H. Kulkarni[1]
[1]Department of Electronics and Telecommunication Engineering, Dr. D. Y. Patil Institute of Technology, Pune, India
[2]Department of Electronics and Telecommunication Engineering, Army Institute of Technology, Pune, India

Article Info

Article history:

Received Mar 28, 2024
Revised Oct 24, 2024
Accepted Oct 31, 2024

Keywords:

Artificial bee colony
Clustering
Cuckoo search algorithm connectivity
Fuzzy C-mean
Gini coefficient
Wireless sensor network

ABSTRACT

Wireless sensor networks (WSNs) are essential for many different types of applications, including industrial, commercial, and agricultural. Inadequate node location, dynamic nodes, network longevity, increased packet drop rates, scaling problems, limited adaptability, and changing climatic conditions pose challenges to the WSN's efficacy. Numerous bio-inspired algorithms have been previously introduced for node placement, demonstrating a significant improvement in data aggregation performance. However, because of the low variability in the solution, weak convergence, and poor balance between exploitation and exploration, the results of WSNs are challenging to interpret. With a unique competitive Cuckoo search algorithm (CCSA), this research presents a connectivity-aware, energy-efficient, and node placement method. Using the elite population to increase the variety of the answer, the suggested competitive strategy aims to enhance convergence. It additionally employs the fuzzy C-mean clustering algorithm. The clustering optimization based on cluster head energy, density, location, Gini coefficients, and other comparable factors uses an artificial bee colony optimization (ABC) algorithm to enhance the clustering and cluster head position. A comparison between the recommended scheme and the traditional state-of-the-art reveals that the suggested system performs better regarding network throughput, residual energy, and network lifetime.

Corresponding Author:

Monica Shivaji Gunjal
Department of Electronics and Telecommunication Engineering, Dr. D. Y. Patil Institute of Technology
Pimpri, Pune, Maharashtra
Email: monicagunjal@gmail.com

1. INTRODUCTION

A wireless sensor network (WSN) is a network of committed sensors that are distributed spatially and track the environmental or physical conditions of the natural world before organizing the data at a control center [1], [2]. WSN is imperative in many applications, such as the internet of things (IoT), disaster management, smart home automation, industrial monitoring, habitat monitoring, transportation, logistics, agriculture monitoring, earthquake detection, and landslide detection. The vast growth in the 5G technology and IoT devices leads to massive growth in the use of WSNs for various data collection, monitoring, control, and communication purposes. The sensor node (SN) performs several tasks, including data acquisition, information flow control, and processing, data storing, data and process synchronization, finding the adjacent node, target tracking, node localization, monitoring, flow control, and promising routing between multiple sensor nodes and base stations [3]. With the help of the wireless link between the nodes, the data acquired from the sensors is propagated to the various sensor nodes. Small clusters comprise the WSN; every cluster contains a cluster head (CH). CHs communicate with the center's main base station (BS) for additional monitoring and action [4], [5].

Mobile WSNs made up of mobile sensor nodes are frequently used in emergencies for environment monitoring and surveillance. The mobile WSN nodes are made up of a radio transceiver, a microcontroller for converting analog signals to digital signals, computing and generating the control signal, and a node that understands the electrical equivalent of the physical inputs such as heat, temperature, moisture, event, pressure, load, and humidity [6], [7]. Determining network lifetime, throughput, scalability, and other performance metrics is very challenging because of the dynamic topology of mobile WSNs. The WSN aims to cooperatively gather data about the professed objects in the monitoring area, transform the monitored data into electrical signals, and broadcast the monitored signals to the BS via wireless multi-hop communication [8], [9]. It has features like self-organized routing, no wiring, a dynamic network, and a potent ability to withstand destruction. It is appropriate for use in various fields, including environmental, medical, and industrial monitoring. Sensor node computing power, energy availability, and battery replacement are all constrained in WSNs. The sensor nodes are generally placed over the surface in an unstructured and structured way. Deploying the nodes over the surface is essential to cover the targets for improving connectivity and efficient data aggregation [10], [11].

Yu *et al.* [12] presented a grey wolf optimization (GWO) algorithm for node placement. It considers network coverage for the node placement. The GWO provides alternatives such as alpha, beta, and omega wolves, where the alpha wolf solution is considered supreme. However, the effectiveness of the placement strategy is limited because less focus is given to energy consumption and network connectivity. Further, Hanh *et al.* [13] suggested a node placement strategy using greedy techniques that collaborate linear programming clustering with graph maximum flow techniques. It considers the connectivity and coverage of the network nodes. Krishnamoorthy *et al.* [14] explored node localization using a neural network (NN) approach. The NN provides the adaptability to cope with the dynamic environment and faster response in mobile network scenarios. However, the network's lifetime is lower because of the mobile scenario. The algorithm focuses only on the localization error. Pu *et al.* [15] provided a Cuckoo search algorithm (CSA) algorithm for the node placement that used a drift strategy. It has provided crucial results for smaller networks, but scalability is less and unsuitable for more extensive area networks [15].

Algorithms that are based on biological phenomena and implemented as computing algorithms are called bio-inspired algorithms [16]. These algorithms can model and solve complicated problems and multi-objective function problem-solving. Several data aggregation schemes' effectiveness demeans in the mobile, heterogeneous, and unstable WSNs [17]. Since sensor nodes need additional power to be mobile, power management is a significant issue with mobile WSNs. The constrained functionality of sensors and the network's application-specific characteristics have led to the progress of current routing algorithms. Data security has received very little attention [18]–[20].

Numerous techniques have been investigated for WSN clustering, mainly focusing on cluster and energy optimization. Clustering is generally performed using the placement and residual power of the nodes. The competence of the clustering scheme is generally observed in terms of mobility, scalability, dependability, dispersion, self-organization, trust, homogeneity, resource awareness, data aggregation, security, and randomized rotation nature [21]–[23]. It is challenging to balance many factors when improving the network settings. There are issues with scalability, energy use, mobility, and network overheads with several clustering approaches. Bio-inspired algorithms are widely employed to handle the various goal functions and complex issue solutions. Several swarm-based algorithms, including, ant colony optimization (ACO), and artificial bee colony (ABC), have been investigated to address the WSN routing issue. These methods can iteratively improve self-effectiveness, tackle complicated problems, and optimize numerous functions simultaneously. The power and routing optimization improved as a consequence of these strategies. Due to their iterative nature, swarm-based algorithms take a long time when the network structure is exceedingly vast. In the sensor network, one-to-one data transfer is the main emphasis of swarm-based routing algorithms. These algorithms rely on arbitrary judgments, which are challenging to conceptually or mathematically describe [24], [25].

However, node deployment is challenging due to the lack of infrastructure, limited sensing and communication range of the sensor, lower node power, and different environmental factors. In this article, we aim to improve the scalability, connectivity, data aggregation, and coverage. This work focuses on minimization of the computational complexity and enhancement in network lifetime.

This article presents the energy-efficient data aggregation scheme focusing on node placement and clustering routing algorithms in the WSN. The chief contributions of this article are summarized as follows:

– A novel competitive Cuckoo search algorithm (CCSA) is proposed for energy efficiency, connectivity, and coverage-aware node placement.

- The competitive strategy in CCSA enhances the diversity of solutions, convergence, and balance between the exploration and exploitation of traditional CSA.
- Implementation of energy-efficient and load-balanced optimized clustering using fuzzy C-means-artificial bee colony (FCM-ABC) algorithm

The effectiveness of the proposed node placement and clustering scheme is evaluated for diverse network conditions using network throughput, residual energy, and network lifetime.

The rest of the article is organized as follows: section 2 provides a survey of node placement and data aggregation schemes utilized in WSN. Section 3 focuses on the details of the proposed scheme's implementation. Further, section 4 elaborates on the network, radio model, CCSA, and FCM-ABC parameters, simulation results, and discussions of results. Lastly, section 5 provides the conclusion and future scopes of the work.

2. METHOD

The flow diagram of the proposed scheme is illustrated in Figure 1, which encompasses network initialization, node placement, clustering, and data aggregation phase. The network scenario is simulated using MATLAB software. The proposed model considers total area of 200×200 m for varying number of nodes between 100 to 500. The initial energy of the nodes is considered homogeneous (0.1J). A novel Cuckoo search algorithm based on a competitive learning strategy is used for node placement. The competitive learning strategy helps to improve the convergence of the CSA algorithm by efficiently using the elite population using competitive learning strategy. The nodes are clustered using the fuzzy C-mean algorithm. The ABC algorithm optimizes the clustering. The outcomes of the proposed scheme is evaluated based on the network lifetime, data throughput, and residual energy.

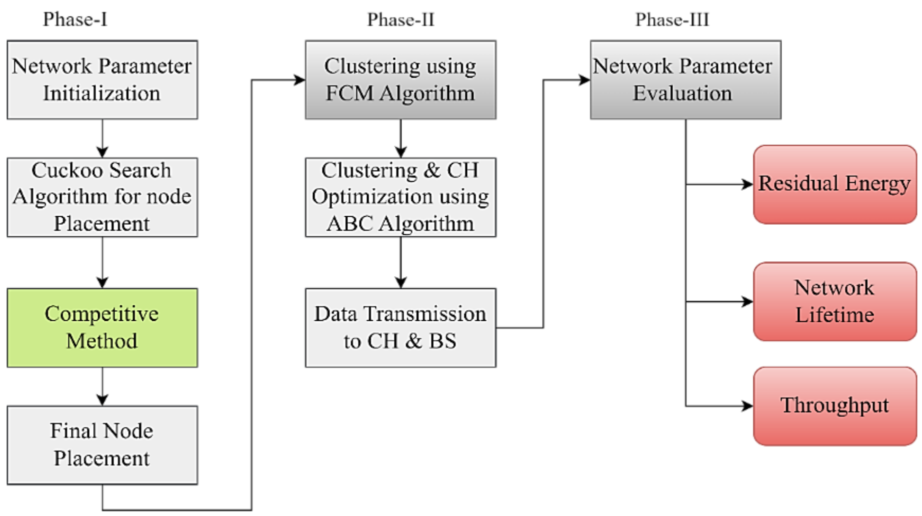


Figure 1. Flow diagram of proposed data aggregation scheme

2.1. Node placement using CCSA

The cuckoo search algorithm is motivated by the natural phenomenon of a cuckoo's egg laying into a nest of other birds. If the host bird identifies that the egg is not laid by it, it throws the egg outside the nest; otherwise, it abandons the nest and builds a new one. Every egg in the nest signifies the possible solution, and the cuckoo egg represents the best, new, and reliable solution. Every nest contains a single cuckoo egg, and every nest with several eggs characterizes the possible solution. The cuckoo searches the nests randomly for laying the egg. The levy flight is considered for the nest-searching behavior of the cuckoo. The proposed competitive learning strategy for CSA selects two members from the elite groups whose fitness is immediately less than that of the best crow fitness. It applies the competition between the two randomly selected elite members from the 5% population with the highest population. The members are interchanged or modified during the competition strategy to form the newer crow population. The fitness for both updated crows is computed after the competition, and the one with the highest fitness is declared the winner. The fitness of the winner member is compared with the fitness of the global best solution. If the fitness of the winner is greater than the fitness of the global best solution, then the winner updates the global best solution.

The competitive learning scheme helps to improve the exploitation of the CSA where the crows having slightly less fitness than the best solution and reutilize it to achieve a better solution. This strategy uses the existing population to enhance convergence.

Step 1: Select two elite members.
P1: Random crow from an elite group
P2: Random crow from an elite group
Step 2: Apply a competitive learning strategy
Step 3: Replace the loser members by winners members of the other group
Step 4: Calculate the fitness of updated P1 and P2
Step 5: $If\ fitness\ (P1)\ >\ Global\_Best\_fitness$
$Global\_Best = P1$
End
$If\ fitness\ (P2)\ >\ Global\_Best\_fitnes$
$Global\_Best = P2$
End

2.2. FCM clustering

The FCM divides the nodes into clusters based on the node positions in the region that is being simulated. It considers the case of a uniform network in which every node has the same beginning energy. The FCM offers the percentage of members present in each cluster that originates from the cluster that is deemed centralized. The value of nodes farther from the centered node is lower, while the degree of nodes closer to the centered node is greater [26]. The nodes are gathered into clusters that have a higher membership function.

2.3. Cluster selection and optimization using ABC

The initial FCM clusters are produced using FCM, and the proposed technique employs the ABC algorithm to perform optimum CH selection from those clusters. The clusters formed by utilizing the FCM method are employed to select optimum CHs with the help of the suggested ANC he uses. The upgraded ABC considers the CH load balancing factor, energy Gini coefficient, CH energy balancing, and intra-cluster and inter-cluster distance for cluster head selection.

Karaboga [27] first conceptualized the bio-inspired phenomena known as ABC in 2005. Three categories of bees are involved in this process: employed, bystanders, and scouts. The worker bees are the ones who find the food sources, the spectator bees are the ones who determine which food source to use, and the scout bees are the ones who hunt for food in random directions after the worker bees are discarded. The count of worker bees is always equal to the count of food sources in the area around the hive. When an employed bee's food supply runs exhausted, it transitions into a scout bee role. Figure 2(a) to 2(d) explains how the CH selection process works inside the ABC algorithm.

The ABC algorithm provides possible SN solutions via random sampling comparable to food sources. Let $\mathrm{SN} = \{\mathrm{S}_1,\ \mathrm{S}_2, \mathrm{S}_3, \dots\dots \mathrm{S}_\mathrm{C}\}$ be the initial bee population. The onlooker uses the probability function for CH selection as given in (3).

$$p_i = \frac{F_i}{\sum_{n=1}^{SN} F_n} \tag{3}$$

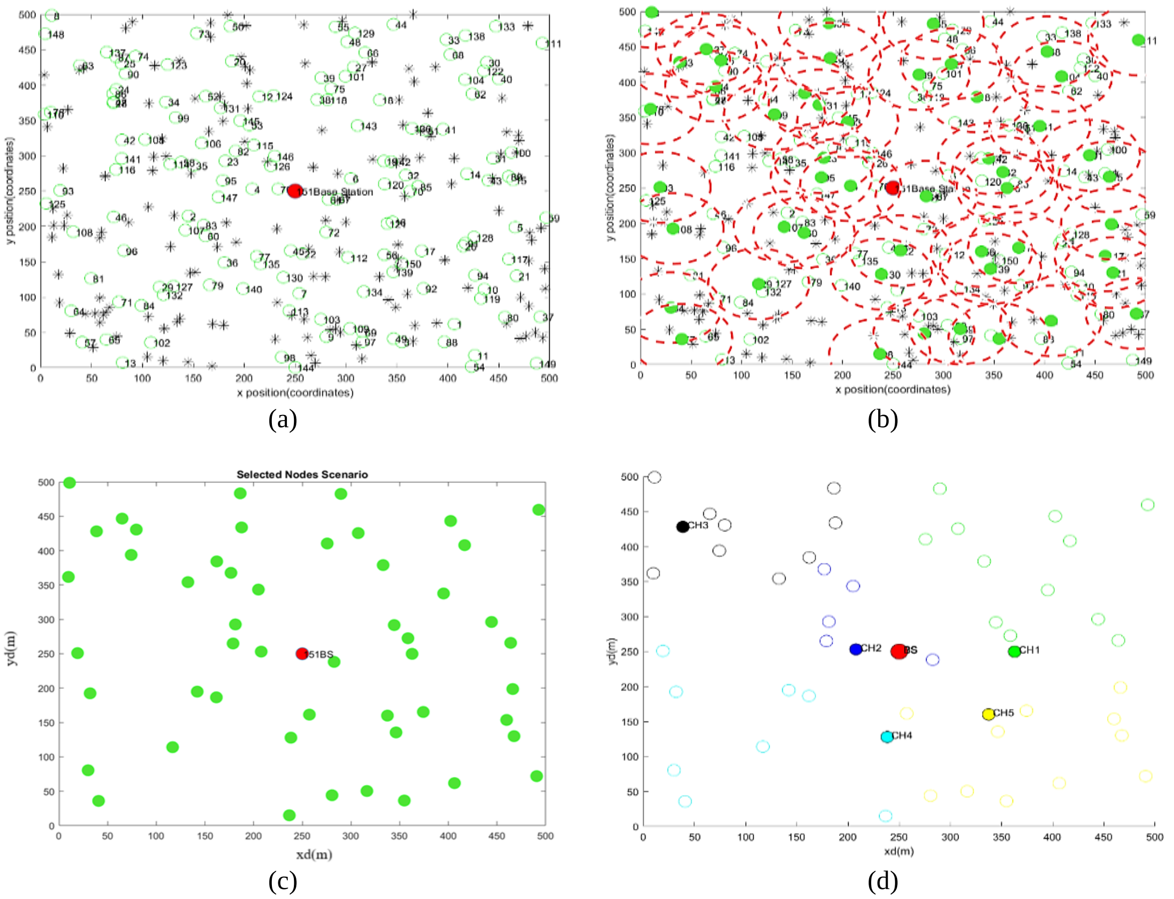
Here, P_i is the probability fitness estimated by onlooker bees, F_i is the fitness of i^{th} solution that is relative to the nectar amount of the food source at position i. The F_i value is determined by the CH load balancing factor, the CH energy balancing factor, the energy Gini coefficient, inter-cluster and intra-cluster distances for CH selection, and the coverage/connectivity of node. Equation (4) provides the fitness function, which specifies that the criterion outlined in (5) must be met for weight factors to be considered fit.

$$F_i = \omega_1 * f_1 + \omega_2 * f_2 + \omega_3 * f_3 + \omega_4 * f_4 + \omega_5 * f_5 \tag{4}$$

$$\omega_1 + \omega_2 + \omega_3 + \omega_4 + \omega_5 = 1 \tag{5}$$

3. RESULTS AND DISCUSSION

The network and radio model simulation parameters are described in Tables 1 and 2, respectively. The initial random node placement scenario is represented in Figure 2(a), and the optimized sensor node (N=50) selected using CCSA to cover 200 targets is shown in Figures 2(b) and 2(c). The cluster head and clustering optimization using the FCM-ABC algorithm is represented in Figure 2(d). The competitive learning strategy helps to select the potential sensor positions that cover the maximum sensor nodes and get connected with the maximum sensor nodes. The suggested scheme covers almost 95%-97% of the simulation area, covering 97%-99% of targets over the simulation area.



(a) (b) (c) (d)

Figure 2. Node placement and using CCSA-FCM-ABC (a) initial random node placement, (b) node selection using CCSA and its coverage, (c) selected nodes using CCSA, and (d) cluttering and CH optimization using FCM-ABC

Table 1. Network simulation parameters

System parameter	Specification
Base station position	Center
Simulation area	200×200 m
Initial energy (Eo)	0.1-0.5 J
Number of nodes	50, 100, 200, 300, …500
Node position	Fixed and mobile
Traffic patterns	Constant bit rate (CBR)

Table 2. Radio model parameters

System parameter	Specification
Threshold distance (do)	$\sqrt{E_{fs}/E_{mps}}$
Energy consumed per bit (E_{elec})	50 nJ /bit
Receiver power consumption (E_{RX})	50 nJ/bit
Transmission power consumption (E_{TX})	50 nJ /bit
Multipath amplification factor (E_{mp})	0.0013pJ/bit/m4
Free space amplification factor (E_{fs})	10pJ/bit/m2
Message bits (K)	2000 bits

Figure 3 provides the simulation scenario for the CCSA-FCM-ABC clustering for various iterations. Figures 3(a) and 3(b) shows the initial scenario and initial FCM clustering. Figures 3(c), 3(d), 3(e) and 3(f) show the clustering optimization simulation for 10^{th}, 30^{th}, 60^{th}, and 100^{th} iterations respectively. It is observed that increasing the iterations helps to achieve better clustering.

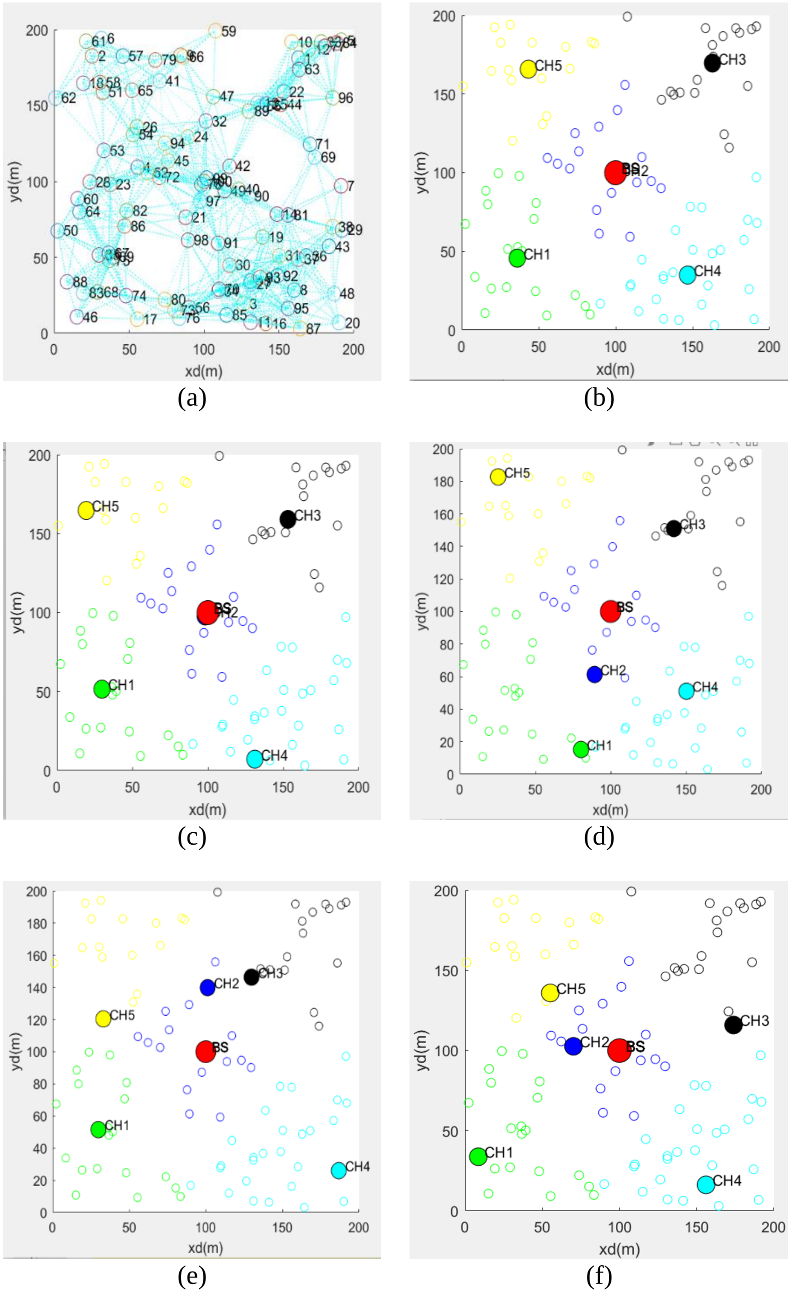


Figure 3. Simulation scenario for various iterations of CCSA-FCM-ABC (a) initial network scenario for selected nodes, (b) FCM clustering, (c) CCSA-FCM-ABC for 10^{th} iteration, (d) CCSA-FCM-ABC for 30^{th} iteration, (e) CCSA-FCM-ABC for 60^{th} iteration; and (f) CCSA-FCM-ABC for 100^{th} iteration

The outcomes of the proposed scheme are compared with the particle swarm optimization (PSO) and genetic algorithm (GA) based node placement strategy based on distinct evaluation metrics. The results are evaluated based on network lifetime (dead and live nodes per round), residual energy, and packet transmitted to CHs and BS. Figure 4 shows the simulation results for the area of 500×500 m, target size of 200, initial energy of 0.1 J and potential sensors positions of 100.

The competitive strategy in CSA helps to enhance the network lifetime over the traditional methods, as given in Figures 4(a) and 4(b). Figure 4(c) illustrates the residual energy of different schemes, which shows that CSA provides more residual energy. Higher residual energy leads to higher total packets transmitted to CHs and BS, as shown in Figures 4(d) and 4(e). The competitive strategy helps to enhance the solution diversity and provides better node deployment compared with traditional CSA. It achieves early convergence and needs a lower deployment time (2.6 sec for 100 nodes).

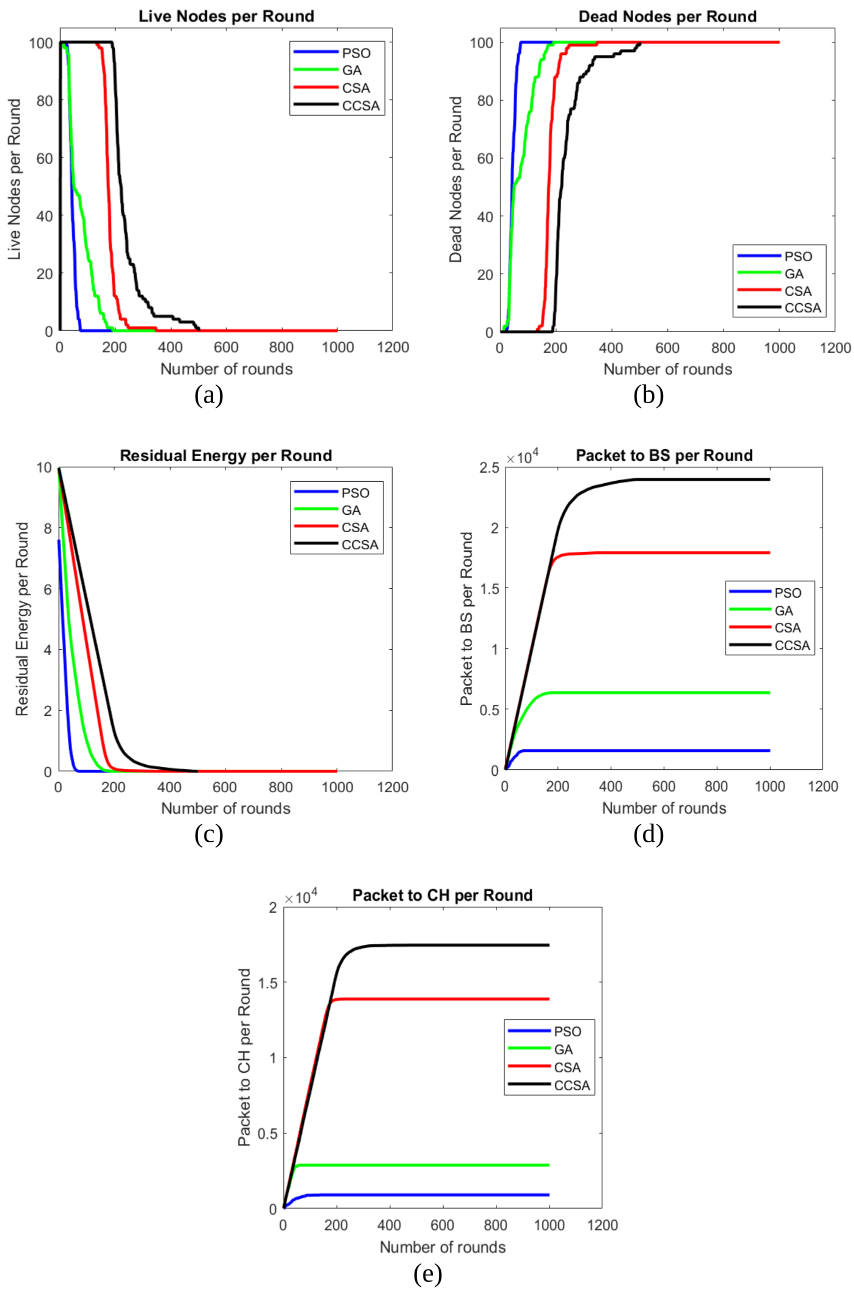


Figure 4. Results of proposed system for different node placement techniques, (a) live nodes per round, (b) dead nodes per round, (c) residual energy, (d) packets to BS, and (e) packets to CHs

The fitness comparison of the CSA, traditional GA, PSO, and proposed CCSA is shown in Figure 5, which shows that the proposed CCSA achieves better convergence compared with the CSA for the 100 iterations. Traditional GA and PSO suffer from poor solution variability and an inferior balance between exploration and exploitation, thus providing poor convergence. The competitive strategy utilized in the CSA helps to enhance the diversity of solutions, balance between exploitation and exploration, and population variability. It effectively utilizes the existing population to enhance the solution diversity and variability, resulting in better CCSA convergence.

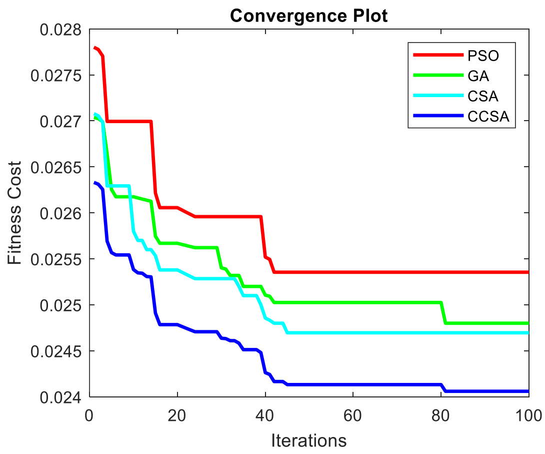


Figure 5. Fitness cost comparison of CSA and CCSA

The novel CCSA-based algorithm provides superior solutions for node placement considering connectivity and coverage. The FCM-ABC-based clustering and CHs optimization provide optimal clustering and help to select the optimal position of the CH in the clusters based on load balancing factor, energy Gini coefficient, CH energy balancing, intra-cluster and inter-cluster distance. Load balancing and energy balancing help improve the network lifetime by distributing equal energy among the cluster nodes. The sensors are optimally selected as the CHs to improve energy efficiency and thus lead to a higher network lifetime. The results of the network lifetime for the different targets are summarized in Table 2. The suggested CCSA-ABC shows a lifetime boost of 51.72% more significant for the first node dead, 35.89% for half node dead, and 29.41% for the last node dead. The competitive learning strategy shows the efficient use of the existing population and helps to provide better node placement that improves the clustering optimization of FCM-ABC. The ABC considers different parameters for the clustering optimization, such as inter-cluster distance, intra-cluster distance, energy Gini, energy balancing, load balancing, connectivity, and network coverage, which helps to enhance the overall network lifetime and network throughput. The proposed method outperforms the existing CSA, GA, and PSO-based node placement scheme regarding the network lifetime, as given in Table 3. The boost in network lifetime of the CCSA-ABC provides superior throughput compared with the CSA, GA, and PSO.

Table 3. Network lifetime comparison

Targets	Algorithm	Number of nodes selected	First dead at round	Half dead at round
200	PSO-ABC	61	62	84
	GA-ABC	58	60	81
	CSA-ABC	55	58	78
	CCSA-ABC	50	28	50
350	PSO-ABC	112	114	134
	GA-ABC	105	104	128
	CSA-ABC	98	95	118
	CCSA-ABC	85	48	80
500	PSO-ABC	126	145	167
	GA-ABC	118	132	158
	CSA-ABC	113	123	148
	CCSA-ABC	102	63	110

Thus, the proposed approach suggests that the data aggregation in the WSN is heavily reliant on the node placement. The proposed CCSA-ABC provides superior results compared with traditional PSO, GA, and CSA-based node placement strategies. The novel CCSA algorithm effectively utilizes the existing elite population to enhance the solution variability and convergence, leading to effective node placement with higher coverage and connectivity.

4. CONCLUSION AND FUTURE SCOPES

This study addresses the issues of poor energy efficiency and short network lifespan in WSNs by providing optimum node placement, clustering, and CH selection using CCSA, Fuzzy C-Mean, and an improved ABC optimization algorithm. The competitive method utilized in CSA for the node placement enhances the algorithm's search space. It improves the algorithm's convergence and needs lower iterations than traditional techniques because of a good balance between exploration and exploitation. The CCSA minimizes the problem of being stuck at local and global minima, increases the population diversity, and solves the algorithm. ACO-based energy-efficient routing helps networks last longer. The ABC considers factors like energy Gini coefficient, load Gini coefficient, and inter-cluster and intra-cluster distance for the best CH selection. It has significantly outperformed the centralized CH selection using the FCM technique in various network density and scalability scenarios. The competitive method utilized in CSA for node placement enhances the algorithm's search space. It improves the algorithm's convergence and needs lower iterations than traditional techniques because of a good balance between exploration and exploitation. The CCSA minimizes the problem of being stuck at local and global minima, increases the population diversity, and solves the algorithm. The CCSA-based node deployment helps enhance scalability, network throughput, network lifetime, and deployment flexibility. It assists in minimizing the complexity of the node deployment algorithm.

In the future, the effectiveness of the suggested strategy may be examined in real-time situations. Future efforts to increase WSN's trustworthiness for dependable data transmission and may take security into account. There is a need to concentrate on reducing the computational intricacy of the method. In the future, the algorithm's effectiveness can be further enhanced by optimal hyperparameter tuning of the CCSA algorithm.

REFERENCES

[1] R. Zagrouba and A. Kardi, "Comparative study of energy efficient routing techniques in wireless sensor networks," *Information*, vol. 12, no. 1, Jan. 2021, doi: 10.3390/info12010042.
[2] H. M. A. Fahmy, "WSNs applications," Springer Nature Switzerland, 2023, pp. 67–242, doi: 10.1007/978-3-031-20709-9_3.
[3] Devika G., A. G. Karegowda, and Ramesh D., "Survey of WSN routing protocols," *International Journal of Applied Evolutionary Computation*, vol. 11, no. 1, pp. 34–51, 2020, doi: 10.4018/ijaec.2020010103.
[4] L. Chan, K. Gomez Chavez, H. Rudolph, and A. Hourani, "Hierarchical routing protocols for wireless sensor network: a compressive survey," *Wireless Networks*, vol. 26, no. 5, pp. 3291–3314, Jul. 2020, doi: 10.1007/s11276-020-02260-z.
[5] M. Shafiq, H. Ashraf, A. Ullah, and S. Tahira, "Systematic literature review on energy efficient routing schemes in WSN – a survey," *Mobile Networks and Applications*, vol. 25, no. 3, pp. 882–895, 2020, doi: 10.1007/s11036-020-01523-5.
[6] S. A. Hussein, "A new wireless sensor networks routing algorithm based on SPIN protocols and circumference technique," *International Journal of Engineering Research and Advanced Technology*, vol. 06, no. 09, pp. 21–27, 2020, doi: 10.31695/IJERAT.2020.3645.
[7] X. Yu, F. Li, T. Li, N. Wu, H. Wang, and H. Zhou, "Trust-based secure directed diffusion routing protocol in WSN," *Journal of Ambient Intelligence and Humanized Computing*, vol. 13, no. 3, pp. 1405–1417, 2022, doi: 10.1007/s12652-020-02638-z.
[8] L. KHEROUA, S. Moussaoui, N. el houda Baroud, and O. Chaib, "An optimized relative coordinates rumor routing (ORCRR) for wireless sensor networks," in *2018 International Conference on Smart Communications in Network Technologies (SaCoNeT)*, Oct. 2018, pp. 312–316, doi: 10.1109/SaCoNeT.2018.8585577.
[9] A. R. Ramos, F. J. Velez, and G. Gardašević, "Performance evaluation of source routing minimum cost forwarding protocol over 6TiSCH applied to the OpenMote-B platform," in *3rd EAI International Conference on IoT in Urban Space*, 2020, pp. 123–134, doi: 10.1007/978-3-030-28925-6_11.
[10] M. E. Migabo, T. O. Olwal, K. Djouani, and A. M. Kurien, "Cooperative and adaptive network coding for gradient based routing in wireless sensor networks with multiple sinks," *Journal of Computer Networks and Communications*, vol. 2017, pp. 1–10, 2017, doi: 10.1155/2017/5301462.
[11] A. R. A. Moundounga, H. Satori, and K. Satori, "An overview of routing techniques in WSNs," in *2020 Fourth International Conference on Intelligent Computing in Data Sciences (ICDS)*, Oct. 2020, pp. 1–7, doi: 10.1109/ICDS50568.2020.9268764.
[12] X. Yu, Y. Duan, Z. Cai, and W. Luo, "An adaptive learning grey wolf optimizer for coverage optimization in WSNs," *Expert Systems with Applications*, vol. 238, 2024, doi: 10.1016/j.eswa.2023.121917.
[13] N. T. Hanh, H. T. T. Binh, V. Q. Truong, N. P. Tan, and H. C. Phap, "Node placement optimization under Q-Coverage and Q-Connectivity constraints in wireless sensor networks," *Journal of Network and Computer Applications*, vol. 212, 2023, doi: 10.1016/j.jnca.2022.103578.
[14] V. K. Krishnamoorthy, U. N. Duraisamy, A. S. Jondhale, J. Lloret, and B. V. Ramasamy, "Energy-constrained target localization scheme for wireless sensor networks using radial basis function neural network," *International Journal of Distributed Sensor Networks*, vol. 2023, 2023, doi: 10.1155/2023/1426430.
[15] Y. Pu, J. Song, M. Wu, X. Xu, and W. Wu, "Node location using cuckoo search algorithm with grouping and drift strategy for WSN," *SSRN Electronic Journal*, 2022, doi: 10.2139/ssrn.4264485.
[16] R. Priyadarshi, S. K. Soni, and P. Sharma, "An enhanced GEAR protocol for wireless sensor networks," in *Nanoelectronics, Circuits and Communication Systems: Proceeding of NCCS 2017*, 2019, pp. 289–297, doi: 10.1007/978-981-13-0776-8_27.
[17] A. Agarwal and A. Dev, "Extended RSSI based cluster head selection algorithm for wireless sensor networks," *International Journal of Future Generation Communication and Networking*, vol. 13, no. 1, pp. 559–568, 2020.
[18] C. A. Grazia, M. Klapez, and M. Casoni, "RONMAN: infrastructured RSSI-based opportunistic routing in mobile Adhoc networks," in *2020 16th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)*, Oct. 2020, pp. 14–19.
[19] X. Fu, G. Fortino, P. Pace, G. Aloi, and W. Li, "Environment-fusion multipath routing protocol for wireless sensor networks," *Information Fusion*, vol. 53, pp. 4–19, Jan. 2020, doi: 10.1016/j.inffus.2019.06.001.

[20] C. Nakas, D. Kandris, and G. Visvardis, "Energy efficient routing in WSNs: a comprehensive survey," *Algorithms*, vol. 13, no. 3, Mar. 2020, doi: 10.3390/a13030072.

[21] S. S. Bhasgi and S. Terdal, "A survey on bio-inspired routing algorithms in wireless sensor network," *International Transaction Journal of Engineering Management & Applied Sciences & Technologies*, vol. 12, no. 2, pp. 1–13, 2021, doi: 10.14456/ITJEMAST.2021.38.

[22] L. Sixu, W. Muqing, and Z. Min, "Particle swarm optimization and artificial bee colony algorithm for clustering and mobile based software-defined wireless sensor networks," *Wireless Networks*, vol. 28, no. 4, pp. 1671–1688, May 2022, doi: 10.1007/s11276-022-02925-x.

[23] J. Sengathir, A. Rajesh, G. Dhiman, S. Vimal, C. A. Yogaraja, and W. Viriyasitavat, "A novel cluster head selection using hybrid artificial bee colony and firefly algorithm for network lifetime and stability in WSNs," *Connection Science*, vol. 34, no. 1, pp. 387–408, Dec. 2022, doi: 10.1080/09540091.2021.2004997.

[24] K. Muthumayil, M. Buvana, and T. Jayasankar, "Energy utilization using artificial bee colony algorithm for network life time enhancement of homogeneous WSNs," *International Journal of Modern Agriculture*, vol. 10, no. 2, pp. 1649–1656, 2021.

[25] M. S. Gunjal and P. H. Kulkarni, "Survey on various aspects of clustering in wireless sensor networks employing classical, optimization, and machine learning techniques," *International Journal on Recent and Innovation Trends in Computing and Communication*, vol. 11, pp. 345–356, 2023, doi: 10.17762/ijritcc.v11i5s.7043.

[26] S. Askari, "Fuzzy C-Means clustering algorithm for data with unequal cluster sizes and contaminated with noise and outliers: Review and development," *Expert Systems with Applications*, vol. 165, p. 113856, Mar. 2021, doi: 10.1016/j.eswa.2020.113856.

[27] D. Karaboga, "An idea based on honey bee swarm for numerical optimization," Computer Engineering Department, Engineering Faculty, Erciyes University, Computer Engineering Department, Engineering Faculty, Erciyes University, Kayseri, Türkiye, TR06, 2005.

BIOGRAPHIES OF AUTHORS

Monica Shivaji Gunjal is currently pursuing her PhD from Dr. D. Y. Patil Institute of Technology, Pune research Centre. She has completed her graduation B.E. (Electronics) and Post graduation M. E. (VLSI and embedded systems) from Savitribai Phule, Pune University, Pune. She has total 12 years of teaching experience under Savitribai Phule, Pune University, Pune affiliated colleges. The author has attended many national and international conferences and has written many research papers. She can be contacted at email: monicagunjal@gmail.com.

Pranodkumar H. Kulkarni is currently working as a professor in the Department of Electronics and Telecommunication Engineering at Dr. D. Y. Patil Institute of Technology, Pimpri, Pune. Pramodkumar H. Kulkarni (India) completed his Ph.D. from Savitribai Phule Pune University in the field of wireless sensor networks in 2019. He has completed his masters in power electronics from Visveswaraya Technological University Belgaum in the year 2006 and BE in electronics and instrumentation from Gulbarga University Gulbarga in the year 1996. Major field of studies is wireless sensor network and related challenges. He has having 09 publications in international conferences and 11 publications in international journals on his name as author. His current research interest areas are wireless sensor network and finding solutions for current challenges in wireless communication within sensor network. Mr. Kulkarni is actively associated with IEEE and IETE bodies and the Fellow member of the same. He can be contacted at email: pramod75kulkarni@gmail.com.