Received: November 4, 2023. Revised: December 1, 2023. 721

International Journal of
Intelligent Engineering & Systems

http://www.inass.org/

Enhanced Cluster Head Selection and Routing in Wireless Sensor Networks Using Fuzzy Logic and Adaptive Cat Swarm Optimization

S. Aramuthakannan[1]* **R Raja Kumar[2]** **G. Mariammal[3]** **M. Geetha[4]**

[1]*Department of Mathematics, PSG Institute of Technology and Applied Research, Coimbatore 641062, India*
[2]*Department of Mathematics, Sathyabama Institute of Science and Technology, Chennai 119 India*
[3]*Department of Computer Science and Engineering, PSNA College of Engineering and Technology, Dindigul, Tamilnadu, India*
[4]*Department of Electrical and Electronics Engineering, Sri Eshwar College of Engineering, Coimbatore, Tamil Nadu, India*
* Corresponding author's Email: sakannan@psgitech.ac.in

Abstract: In a wireless sensor network (WSN), there are sets of autonomous sensor nodes distributed spatially that use wireless communication to track and document physical or environmental aspects. The series of sensor nodes (SN) cannot be changed when it is installed in an isolated or unattended region due to their wireless nature. Because of the high energy restrictions of wireless sensor devices, it is crucial to carefully manage extreme energy consumption by malevolent nodes in order to enhance network performance. To overcome this challenge fuzzy based adaptive cat swarm optimization for routing (FAR) has been proposed to decrease latency, increase network lives, and minimize energy consumption by reducing the network's energy consumption. There are two stages to the proposed FAR approach. In the first stage, the choice of the cluster head is made depending on things like energy, distance, and transmission cost using fuzzy logic. In the second stage, an adaptive cat swarm optimization method is used to choose the most efficient route for packet routing to maximize node lifetime and to ensure efficient packet routing. The effectiveness of the proposed FAR strategy has been established using metrics like packet delivery, lifetime, and energy efficiency for evaluation. According to the experimental findings, the suggested FAR model consumes less energy than the current FCEEC (fully connected energy-efficient clustering), HSA-CSO (harmony search algorithm and competitive swarm optimisation), and EECHIGWO (energy-efficient cluster head selection using a grey wolf optimization algorithm) models by 43.4%, 32.5%, and 24.1% respectively.

Keywords: Wireless sensor network, Adaptive cat swarm optimization, Fuzzy logic, Routing, Cluster head selection.

1. Introduction

In wireless sensor networks (WSN), there are SN that track different applications and gather environmental data [1]. The sensors in the network are tiny nodes that are randomly dispersed. In this deployment, data is remotely perceived and transmitted for decision-making to the system or end-user [2]. They collect signals from their surroundings and send the information they have obtained to the base station (BS).

Small batteries in SN are expensive to replace or recharge in complicated situations. Data transmission and collection must be performed at each node using the least amount of energy possible to increase the longevity of the WSN [3]. To increase the longevity of the sensor nodes, they are arranged into clusters. The individual overseeing each cluster, referred to as the cluster head (CH), makes arrangements for the cluster members to collect data. CH functions in three stages. gathers data from a cluster member (CM), analyses it, and finally sends the finished product to the business server (BS) [4, 5].

WSN's influence on the use of power-efficient routing techniques is one of its key objectives. As a

Received: November 4, 2023. Revised: December 1, 2023.

result, choosing the right CH increases the lifespan of WSNs and is crucial for energy conservation [6-10]. This research proposes fuzzy based adaptive cat swarm for routing (FAR) approach to reduce latency and energy use and lengthen network lifetime. The proposed FAR system's primary contributions are as follows:

- There are two stages to the suggested FAR approach. The first stage includes cluster head selection, while the second stage includes optimal routing.
- Fuzzy logic is used to choose the CH based on factors including, transmission cost, energy use, and distance
- An adaptive cat swarm optimization technique is hired to choose the best path and extend the node's lifespan for efficient data packet routing.
- Evaluation variables like packet delivery, network lifetime, and energy efficiency have been used to establish the effectiveness of the proposed FAR method.

The following explanations apply to the remaining sections of this study: The analysis of the study is based on the literature in section 2. Section 3 provides a detailed discussion of the suggested FAR methodology. Section 4 presents the results and discussion, while section 5 presents the conclusion.

2. Literature survey

In 2020, Baradaran, A. A. and Navi, K., [11] suggested a high-quality clustering algorithm (HQCA) to build high-quality clusters, and fuzzy logic is used to select the best CH. The HQCA-WSN approach has been shown through simulation results to dramatically reduce energy usage and increase network lifetime. They might not be able to adjust well to changing environmental circumstances or dynamic network settings.

In 2021, Panchal, A. and Singh, R. K., [12] EADCR, or energy aware distance-based cluster head selection and routing, is a suggested method to lengthen the lifespan of the system. The EADCR achieves improvement in terms of the remaining energy, coverage, and system era. Because CH is frequently chosen based only on distance, the EADCR technique may result in high energy consumption.

In 2021, Khot, P. S. and Naik, U., [13] suggested particle-water wave optimization (P-WWO) to guarantee a safe data packet routing technique. The average energy remaining, active nodes, coverage, and energy balancing index which had values of 0.9246%, 144, 99.9%, and 0.666 J correspondingly, all demonstrated that P-WWO performed better.

In 2022, Narayan, V. and Daniel, A. K., [14] suggested the fuzzy cluster head selection (FBCHS) protocol as a way to give the sensor network an efficient routing method. The FBCHS protocol's results are compared to those of the SEP procedure and show improvements in the system's overall performance and stability timeframe. It can be difficult and time-consuming to implement genetic algorithms for CH assortment.

In 2022, Roberts, M. K. and Ramasamy, P.,[15] introduced the energy-efficient cluster-based routing protocol (GEIGOA) to address problems with the CH assortment process, maintaining the energy stability of the system and increasing its longevity. The result demonstrates that the suggested GEIGOA scheme outperforms benchmarked CH selection strategies in terms of boosting stability and longevity while lowering instability.

In 2022, Yadav, R. K. and Mahapatra, R. P.,[16] proposed a new hybrid optimization algorithm-based ordered routing in the WSN basis for energy-conscious CH selection. According to the results, the normalized energy of the suggested PDU-SLnO approach was higher. However, there are still certain problems, such as a poor exploitation phase and a slow convergence rate.

In 2022, G. C. Jagan and P. Jesu Jayarin.,[17] outlined a fully connected energy-efficient clustering (FCEEC) method to ascertain the straight track of the multi-hop configuration that leads from the SN to the CH. When compared to certain conventional methods for CH selection, the results showed enhanced performance measures like energy efficiency, packet delivery, network latency, and dead node count.

In 2022, Kumar, A., et al.,[18] suggested a combination of competitive swarm optimization (CSO) and harmony search algorithm (HSA) to select an energy-efficient CH, providing a worldwide search for quick convergence rates. The result shows that by reducing energy use, the suggested routing method lengthens the lifespan of the network.

In 2022, Kathiroli, P. and Selvadurai, K., [19] proposed a hybrid sparrow search approach that utilizes a differential evolution method to report the energy efficiency issue in WSNs and choose a cluster head. Compared to earlier algorithms, it shows gains in throughput and residual power. When trying to improve performance, it can run into coverage and connectivity problems.

In 2023, Rami Reddy, M., et al.,[20] proposed an enhanced GWO (EECHIGWO) approach has been to build an energy-efficient cluster head selection

Table 1. Comparison of existing methods

AUTHORS	METHODS	ADVANTAGES	DISADVANTAGES
Baradaran, A.A. and Navi, K., [11]	HQCA, or high-quality clustering algorithm	strong dependability, a low clustering error rate, and improved scalability.	complexity to the clustering and CH selection procedure.
Panchal, A. and Singh, R.K., [12]	(EADCR) Energy-aware Distance-based Cluster Head Routing and Selection	Scalability is offered by EADCR by creating clusters based on distance.	energy utilization is high as a result of frequent CH selection.
Naik, U. and Khot, P.S. [13]	P-WWO, or particle-water wave optimization	The protocol improves security by choosing stable and trustworthy nodes as CH	Increased processing time and resource use.
Narayan, V. and Daniel, A.K., [14]	The FBCHS protocol, or fuzzy-based cluster head selection	The network's overall performance and stability period are enhanced.	Time consuming,
Roberts, M.K. and Ramasamy, P., [15]	(GEIGOA) Energy-efficient cluster-based routing protocol	scalability, fault tolerance, reduced latency, increased network lifetime, energy efficiency, load balancing, and flexibility,	Implementing and maintaining the protocol could become more difficult due to the increased complexity.
Yadav, R.K. and Mahapatra, R.P., [16]	The algorithm known as Particle Distance Updated Sea Lion Optimization (PDU-SLnO)	High convergence rates for exploitation capabilities and search effectiveness.	Determining the best values for the parameters can be time-consuming and challenging.
Jagan, G.C. and Jesu Jayarin, P., [17]	The mechanism of fully linked energy-efficient clustering, or FCEEC	Node energy efficiency has greatly improved, improving the packet delivery rate.	The method may become less effective and efficient as the network grows.
Kumar, A., et al., [18]	Combining Competitive Swarm Optimization (CSO) with the Harmony Search Algorithm (HSA)	Convergence speed, increased energy efficiency, robustness to changing network conditions, and customizability potential.	Harder to validate, Computational requirements may increase significantly.
Kathiroli, P. and Selvadurai, K., [19]	a Differential Evolution method combined with a hybrid Sparrow search strategy	Improvements in residual energy and throughput.	Lower coverage, and connectivity issues.
Rami Reddy, M., et al., [20]	algorithm based on ECHIGWO	It improves the WSNs' average throughput, network stability, energy efficiency, and longevity.	Nevertheless, there are certain drawbacks, including feature execution and accuracy.

strategy that looks into the differences between exploration and exploitation. By employing the lowest energy levels in WSNs, the outcomes validated the decision to use the most energy-efficient cluster head, corrected premature convergence, and enhanced network longevity.

Several related studies have been conducted to reduce latency and energy use and lengthen network lifetime. Moreover, there are a number of disadvantages in the existing methods like complexity, high energy utilization, time consumption, lower coverage, etc. This paper proposed a FAR technique to eliminate these disadvantages, which is given in the following section. Table 1. Depicts the comparison of existing methods.

3. Proposed method

In this research, fuzzy based adaptive car swarm optimization for routing (FAR) method has been proposed to reduce energy use, reduce latency, and lengthen network lifetime. There are two stages to the

Received: November 4, 2023. Revised: December 1, 2023.

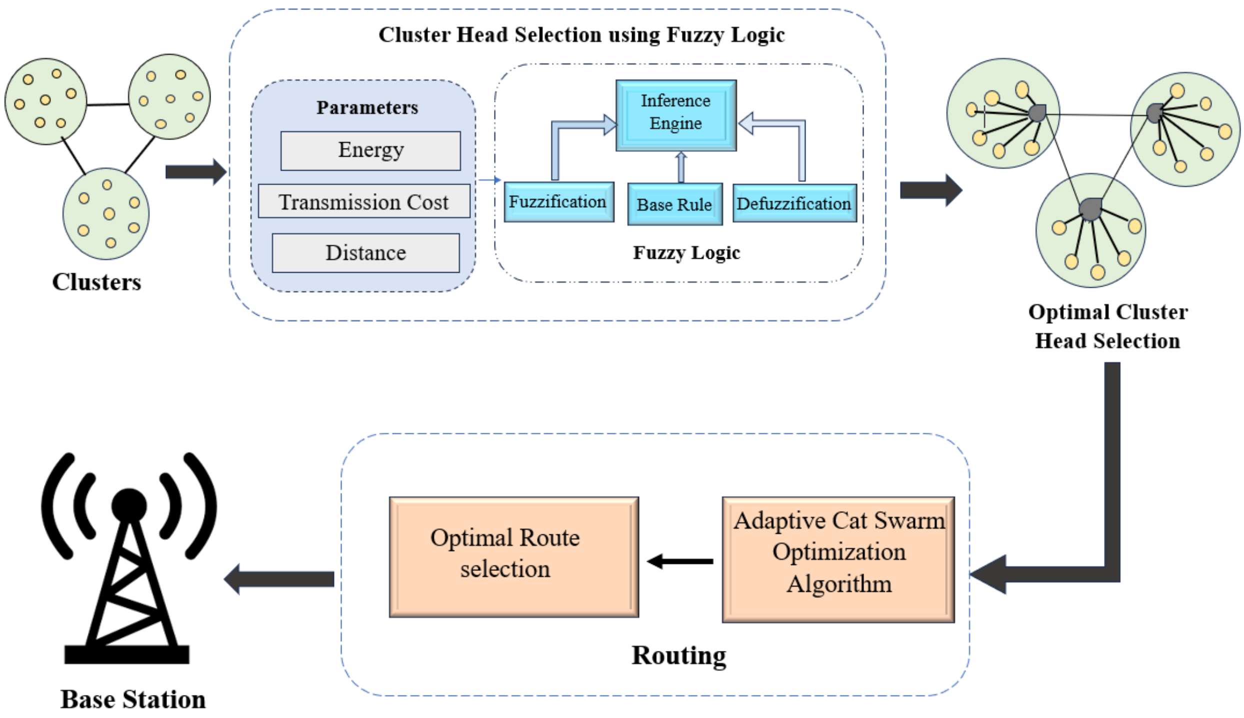

Figure. 1 The proposed architecture of FAR

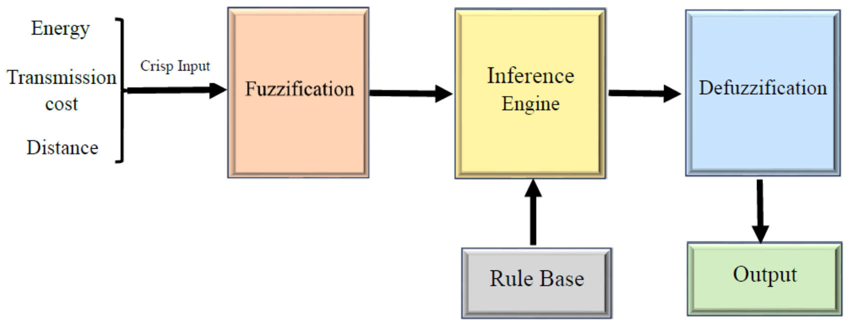

Figure. 2 Fuzzy logics

proposed FAR approach. The first stage includes cluster head selection and the second stage includes optimal routing. Using fuzzy logic, the first stage determines which CH to employ for a given node depending on factors including energy, transmission costs, and distance. Adaptive cat swarm optimization is employed in the second stage to regulate the ideal route for effective data packet routing and to prolong the node's lifespan. The proposed workflow is shown in Fig. 1.

3.1 Cluster head selection

The purpose of cluster head selection is to determine, using a set of criteria or metrics, which node is most suited to serve as the cluster head. The CH election mechanism using fuzzy logic protocol extends the network lifetime of WSNs utilizing fuzzy logic. Three fuzzy parameters are used in CH selection: energy, transmission cost, and distance. Fuzzification, an inference system, a rules basis, and defuzzification are all components of fuzzy logic. Fig. 2 depicts the general fuzzy logic system's structure.

3.1.1. Fuzzification

Fuzzification, a crucial phase in fuzzy logic, enables the transformation of precise or crisp inputs into fuzzy representations, enabling the modeling and analysis of systems with uncertainty and imprecision. It is achieved by simply recognizing that a large number of quantities that are commonly perceived as crisp and deterministic are actually highly uncertain. The variable is likely fuzzy if the form of uncertainty is caused by imprecision, ambiguity, or vagueness, and may be represented by a membership function, which is an essential part of a fuzzy set.

Received: November 4, 2023. Revised: December 1, 2023.

Table 2. Fuzzy rules

RULES	ENERGY	TRANSMISSION COST	DISTANCE	CHANCE
1	Lo	L	Cl	M
2	Lo	L	Ad	Le
3	Lo	L	F	Le
4	Lo	Av	Cl	M
5	Lo	Av	Ad	M
6	Lo	Av	F	Le
7	Lo	S	Cl	Mo
8	Lo	S	Ad	M
9	Lo	S	F	M
10	Me	L	Cl	M
11	Me	L	Ad	M
12	Me	L	F	Le
13	Me	Av	Cl	M
14	Me	Av	Ad	M
15	Me	Av	F	Le
16	Me	S	Cl	Mo
17	Me	S	Ad	M
18	Me	S	F	M
19	H	L	Cl	M
20	H	L	Ad	M
21	H	L	F	Le
22	H	Av	Cl	M
23	H	Av	Ad	M
24	H	Av	F	Le
25	H	S	Cl	Mo
26	H	S	Ad	M
27	H	S	F	M

3.1.2 Inference engine

Each input variable has three linguistic states, and the inference engine processes fuzzy values using a rule base and other methodologies. This yields 27 fuzzy inference rules in total, with three states for each of the three factors. The three levels and the total number of nodes in a network are depicted by language variables. There are three different classifications for transmission costs: large, average, and small; energy, high, medium, and low; and distance, close, adequate, and far. Table 2 provides specifics on cluster-head election decisions made using probability for different input factors.

Table 2 enumerates the 27 rules pertaining to the three variables. In order to create fuzzy production rules based on the fuzzy rules, the three parameters are used as inputs for fuzzy variables. The probability that a sensor node will take over as the cluster head is represented by the output variables. The possibility of sensor nodes serving as cluster heads increases with output. This structure was used to select CH at each layer. The sensor nodes selected to be the CH have the greatest fitness rank. A key idea in fuzzy logic is the membership function, which describes how much an element belongs to a fuzzy set. It converts an input value to a membership degree, which indicates how closely the value resembles the traits listed in the fuzzy set. When given a numerical input value, a membership function will normally award it a membership degree between 0 and 1, indicating the degree to which the value is a member of a specific fuzzy set. Parameters with range are shown in Table 3. There are numerous membership function models, including sigmoidal, gaussian, s-shape, and z-shape. However, the triangle membership function is used in this strategy to cut down on calculation costs. The fuzzy membership function for output is depicted in Fig.3.

3.1.3. Defuzzification

The defuzzifier transforms a fuzzy set into an exact integer by operating on the fuzzy solution space.

Table 3. Range-related parameters

Parameter for Fuzzy Input	Range		
Energy	0-0.4	0.35-0.7	0.65-9
	Low (Lo)	Medium (Me)	High (H)
Transmission Cost	0.2-0.45	0.35-0.75	0.7-0.85
	Large (L)	Average (Av)	Small (S)
Distance	0.1-0.35	0.3-0.5	0.45-8
	Close (Cl)	Adeq (Ad)	Far (F)
Output	0.15-0.5	0.45-0.8	0.7-1
	Less (Le)	Medium (M)	More (Mo)

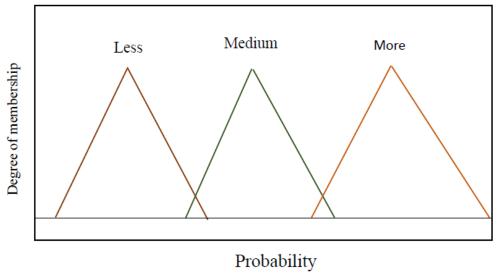

Figure. 3 Membership function for output

Selecting an acceptable defuzzification method can be based on empirical or axiomatic reasoning, and it requires taking computing effort into account. The three most popular defuzzifiers are the maximum methods, the center of gravity, and the center of singleton. The center of gravity (COG) method is the defuzzification approach in this instance. In practical applications, the coefficient of determination (COG) is often employed to get the most accurate value of a fuzzy quantity by computing the weighted average of the membership function. COG over a sample of points is calculated by applying formula (1) to the aggregate output membership function.

$$COG = (\sum \mu_b(z) \times z)/(\sum \mu_b(z)) \tag{1}$$

Here, z represents the range of possible input values, $\mu_b(z)$ is the Membership function of value z.

3.2 Optimal routing

Knowing that increasing WSN lifetime is a top priority due to power-constrained sensor nodes, For every real-time WSN application, developing an efficient routing protocol is critical. In this research, adaptive cat swarm optimization (ACSO) is used for optimal routing. ASCO is a metaheuristic optimization technique that is developed as a result of cat hunting behavior. To determine which data transfer path is optimal, it combines the exploitation and exploration capabilities of optimization using swarms of particles PSO and cats CSO. The two primary procedures used by the ACSO are tracing mode. seeking mode.

Seeking Mode:

Cats are provided in a searching mode. The cats are now scanning the area and slightly shifting their positions. In this, the cats are looking for the best data transmission routing. The ACSO algorithm includes four parameters: self-position consideration (SP), counting various dimensions (CD), searching memory pool (MP), and seeking collection of selected dimensions (SD). The following is a description of the search mode:

Step 1: Create MP copies of the ith solution (cat).

Step 2: Update each copy's position according on the parameter CD by arbitrarily adding or subtracting SD percent from the value of the current position.

Step 3: Calculate the fitness values for each copy.

Step 4: Choose the best candidate for the ith cat slot from among the MP copies.

If the FV values for the fitness function are not all exactly identical. Calculate the selection probability for each solution using (2)

$$p_c = \frac{|FV_i - FV_j|}{FV_{max} - FV_{min}} \tag{2}$$

Here, P_c denotes probability of the newest cat, FV_i is the fitness value of each cat, FV_{max} indicates maximum evaluation of fitness value and FV_{min} is minimum evaluation of fitness value

Tracing mode:

The tracing mode refers to the state where the target is being tracked after being located. Three steps can be used to briefly illustrate this action. Following are the steps:

Step 1: Update the velocity of each Cat $_a$. The equation states:

$$V_a = V_{a,d} + K \times C(Y_{best,d} - Y_{a,d}) \tag{3}$$

Here, $V_{a,d}$ is speed of cat a in length d, K is Arbitrary numeral, C is Constant, $Y_{best,d}$ is Cat's location with best outcome, $Y_{a,d}$ is Cat's current location.

Step 2: Verify that the speeds are within the permitted range of speeds.

Step 3: Update the position of the cat$_a$

$$Y_a = Y_{a,d} + V_{a,d} \tag{4}$$

Received: November 4, 2023. Revised: December 1, 2023.

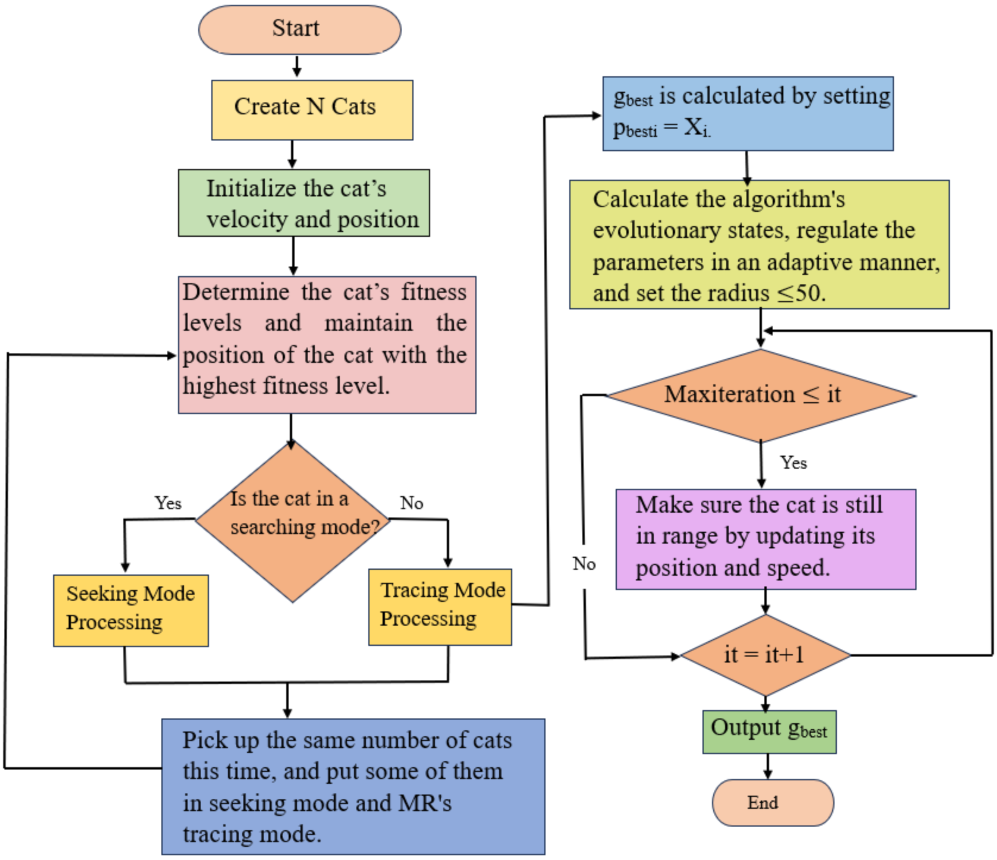

Figure. 4 Flow chart of ASCO

3.2.1 Adaptive cat swarm optimization

The metaheuristic optimization technique known as ASCO (adaptive cat swarm optimization) was created in response to cat hunting behavior. In order to ascertain the best route for data transport, it combines the exploitation and exploration capabilities of optimisation using swarms of particles (PSO) and cats (CSO).

In search position radius range is added:

When the gap between $Y_{a,d}$, and $g_{d,best}$ is smaller than the area, the distinct $Y_{a,d}$ moves closer to $g_{d,best}$. Simply deviate it from $p_{d,best}$ when the remoteness among $Y_{a,d}$ and $p_{d,best}$ is fewer than the area. The following equations determine the value of the elements.

$$V_a=\omega . V_{a,d}+K_1 \times C_1\left(p_{best,d}-Y_{a,d}\right)+ K_2 \times C_2\left(g_{best,d}-Y_{a,d}\right)+\mathrm{f}\cdot E_i+\mathrm{e}\cdot F_i \tag{5}$$

where f and e represent the masses drawn towards and away after the local and global optimal solutions, individually. Fi and Ei represent the sources of food for the ith individual and ith individual's enemy.

Fig.4 depicts the complete flow chart of ASCO. First, initialize each cat at randomly. Next, determine the fitness value. Making its parameters adaptive and

Algorithm 1: ASCO algorithm for routing

Start
I/p: cat sum C_i (i= 1, 2, . . ., m), r, and PS
while
determine the cat's overall fitness function.
C_b = finest key for cat
while i > N
If PS = 1
Start Seeking mode
Else
Start Tracing mode
Terminate If
Terminate while
Identify improved results
Terminate

Table 4. Simulation parameters

Parameters	Values
Size of Network	500mX500m
No. of Nodes	500
Initial Energy	100J
Packet Size	5000 bits
Transmission Power	1.8W
Channel Type	Wireless
Simulation Time	800s

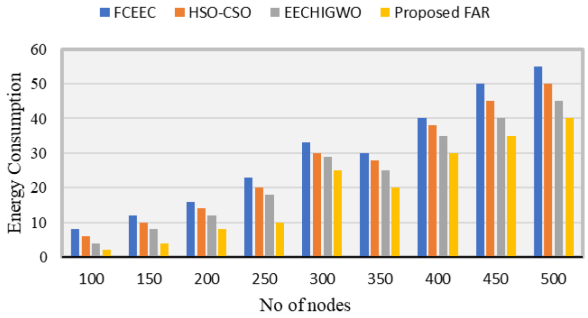

Figure. 5 Energy consumption Vs No of nodes

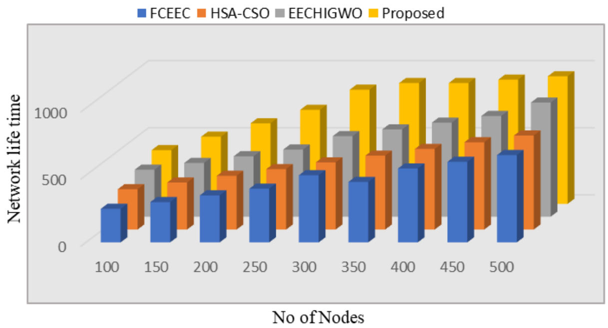

Figure. 7 Network lifetime Vs No of nodes

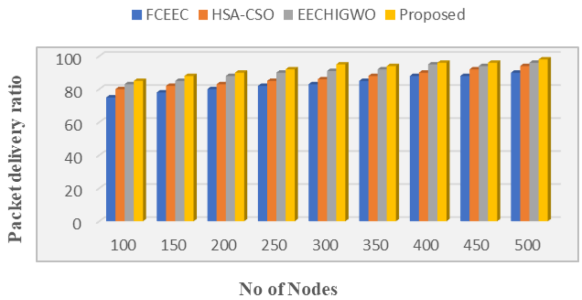

Figure. 6 Packet delivery ratio Vs No of nodes

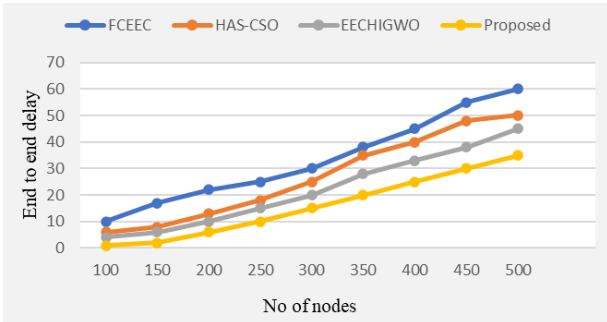

Figure. 8 End-to-end delay Vs No of nodes

adjustable in the tracing mode is the final step.

The ACSO pseudocode is displayed in Algorithm 1.

Termination criteria: It is only terminated if the maximum number of iterations have been finished, this excellent solution-based VM has been set up in PM using the upgraded best fitness value that was selected.

4. Result and discussion

The experimental results of the proposed methodology are analyzed and a discussion of performance is done in terms of numerous evaluation metrics in this section. The proposed approach is implemented in the network simulator (NS2) with a RAM of 4 GB, and a Core processor by Intel was chosen. Table 4 lists the predetermined simulation parameters.

4.1 Comparative analysis

This section includes simulations to evaluate the effectiveness of the suggested FAR technique. The FCEEC [17], HSA-CSO [18], and EECHIGWO [20] protocols are contrasted with the suggested protocol. A number of criteria, including throughput, packet delivery rate, length of the network, end-to-end delay, and energy use are utilized to assess the FAR protocol.

The way in which energy consumption rises with node count is much more evident in Fig. 5. With 500 nodes instead of 100, the new FAR model is compared with current methods based on overall energy use. From Fig. 5, it can be shown that the suggested FAR uses less energy than the other three traditional approaches combined.

From Fig. 6, the performance of the packet delivery ratio is analyzed using the FAR model in comparison to existing approaches FCEEC [17], HSA-CSO [18], and EECHIGWO [20]. There are varying numbers of sensor nodes—from 0 to 500. Fig. 6 demonstrates that. Comparing the proposed system to the existing systems, it exhibits higher packet delivery ratio values for various numbers of sensor nodes.

Based on Fig. 7, the FAR model analyzes the system period's performance in relation to the current methods FCEEC [17], HSA-CSO [18], and EECHIGWO [20].

In comparison to the FCEEC model, the typical network lifespan is 39.7%, whilst the typical network lifetimes for the HSA-CSO model and the EECHIGWO model are 33.0% and 21.9% respectively, with the suggested model having a greater average network lifetime of 50.70%.

Fig. 8 illustrates the performance analysis of a complete delay using FAR and existing techniques FCEEC [17], HSA-CSO [18], and EECHIGWO [20]. The traditional FCEEC, HSA-CSO, and EECHIGWO on the other hand, yield a long period to find the endpoint node. It demonstrates how FAR shortens transmission times and consistently seeks out intermediary nodes that meet the needed criteria.

The throughput is shown in Fig. 9 for various

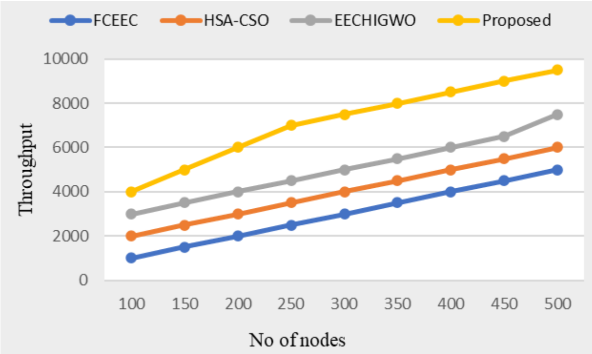

Figure. 9 Throughput Vs No of nodes

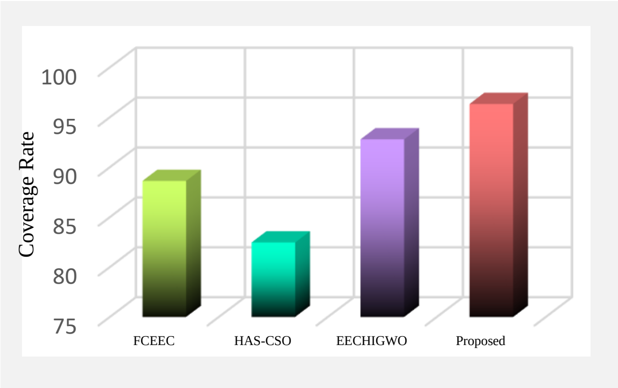

Figure. 10 Comparison in terms of coverage rate

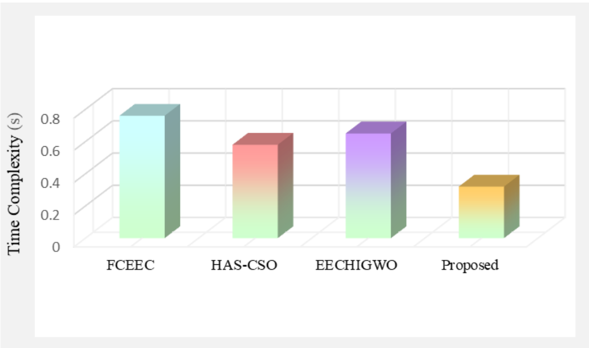

Figure. 11 Comparison in terms of time complexity

node counts. Comparing the proposed FAR protocol to the existing methods FCEEC [17], HSA-CSO [18], and EECHIGWO [20] reveals that it has a better average throughput. The average throughput of the suggested approach is 32.8%, 24.7%, and 19.5% higher than that of the existing methodologies.

Fig. 10 shows the comparison of coverage rate with existing FCEEC [17], HSA-CSO [18], and EECHIGWO [20] methods and the proposed FAR technique. It shows that the proposed FAR technique has the highest coverage rate associated to the current systems.

The coverage rate of the proposed FAR method is increased by 3.68%, 14.4%, and 8.02% when compared to existing FCEEC, HSA-CSO, and EECHIGWO techniques respectively.

Fig. 11 presents a time-based complexity comparison between the proposed FAR methodology and the current FCEEC [17], HSA-CSO [18], and EECHIGWO [20] methods. It demonstrates that the suggested FAR approach has lower time-based complexity than the FCEEC, HSA-CSO, and EECHIGWO methods that are already in use, respectively.

4.2 Discussion

Our study's findings show that the FAR technique WSNs was developed and implemented successfully. In terms of energy consumption, our FAR model outperformed current methods (FCEEC, HSA-CSO, EECHIGWO) by 43.4%, 32.5%, and 24.1%, respectively, showcasing its energy efficiency. The network lifetime was increased by 39.7%, 33.0%, and 21.9%, exceeding the comparative models' capacity. In FAR, the throughput, end-to-end delay packet, and delivery ratio all performed better. Furthermore, the proposed FAR technique demonstrated a higher coverage rate, and its time complexity was found to be lower than existing methods, ensuring efficient and timely processing. The results indicate that FAR is a robust solution for enhancing the overall presentation of WSN, providing energy savings, extended network lifetime, and improved routing efficiency.

5. Conclusion

In this research, fuzzy-based adaptive cat swarm optimization for routing has been proposed. There are three stages to the proposed approach. In the first phase, using fuzzy logic, the CH is chosen based on factors like distance, energy, and transmission cost. Fuzzification, an inference system, a rules basis, and defuzzification are all components of fuzzy logic. In the second stage, an adaptive cat swarm optimization technique is utilized to determine the optimum path for data packet routing that is efficient and extends node life. Utilizing evaluation indicators such network lifetime packet delivery, energy efficiency, and lifetime packet delivery, the efficacy of the proposed FAR method has been established. According to the experimental findings, the proposed FAR model consumes less energy than the current FCEEC, HSA-CSO, and EECHIGWO models by 43.4%, 32.5%, and 24.1% respectively. The proposed method advances the network period by 39.7%, 33.08%, and 21.9% better than FCEEC, HAS-CSO, and EECHIGWO respectively. Future work will focus on developing hybrid models that integrate fuzzy logic with machine learning techniques to enhance decision-making and resource management in WSNs.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

For research articles with several authors, a short paragraph specifying their individual contributions must be provided. The following statements should be used as follows: "Conceptualization, S. Aramuthakannan and R Raja Kumar; methodology, G. Mariammal; software, M. Geetha; validation, S. Aramuthakannan, R Raja Kumar, and G. Mariammal; formal analysis, M. Geetha; investigation, S. Aramuthakannan; resources, R Raja Kumar; data curation, R Raja Kumar; writing—original draft preparation, M. Geetha; writing—review and editing, S. Aramuthakannan; visualization, R Raja Kumar; supervision, XXX; project administration, G. Mariammal; funding acquisition, M. Geetha", etc. Authorship must be limited to those who have contributed substantially to the work reported.

Acknowledgments

The author would like to express his heartfelt gratitude to the supervisor for his guidance and unwavering support during this research for his guidance and support.

References

[1] V. Narayan, A. K. Daniel, and P. Chaturvedi, "E-FEERP: Enhanced Fuzzy based Energy Efficient Routing Protocol for Wireless Sensor Networks", *Wireless Personal Communications*, pp. 1-28, 2023.

[2] O. I. Khalaf, C. A. T. Romero, S. Hassan, and M. T. Iqbal, "Mitigating hotspot issues in heterogeneous wireless sensor networks", *Journal of Sensors*, pp. 1-14, 2022.

[3] M. Gamal, N. E. Mekky, H. H. Soliman, and N. A. Hikal, "Enhancing the lifetime of wireless sensor networks using fuzzy logic LEACH technique-based particle swarm optimization", *IEEE Access*, Vol. 10, pp. 36935-36948, 2022.

[4] S. Chaurasia, K. Kumar, and N. Kumar, "MOCRAW: A Meta-heuristic Optimized Cluster head selection-based Routing Algorithm for WSNs", *Ad Hoc Networks*, p. 103079, 2023.

[5] M. Kaedi, A. Bohlooli, and R. Pakrooh, "Simultaneous optimization of cluster head selection and inter-cluster routing in wireless sensor networks using a 2-level genetic algorithm", *Applied Soft Computing*, Vol. 128, p. 109444, 2022.

[6] R. Punithavathi, C. Kurangi, S. P. Balamurugan, I. V. Pustokhina, D. A. Pustokhin, and K. Shankar. "Hybrid BWO-IACO Algorithm for Cluster Based Routing in Wireless Sensor Networks", *Computers, Materials & Continua*, Vol. 69, No. 1, 2021.

[7] P. K. Poonguzhali and N. P. Ananthamoorthy, "Improved energy efficient WSN using ACO based HSA for optimal cluster head selection", *Peer-to-Peer Networking and Applications*, Vol. 13, pp. 1102-1108, 2020.

[8] J. Daniel, S. F. V. Francis, and S. Velliangiri, "Cluster head selection in wireless sensor network using tunicate swarm butterfly optimization algorithm", *Wireless Networks*, Vol. 27, pp. 5245-5262, 2021.

[9] J. John and P. Rodrigues, "MOTCO: Multi-objective Taylor crow optimization algorithm for cluster head selection in energy aware wireless sensor network", *Mobile Networks and Applications*, Vol. 24, No. 5, pp. 1509-1525, 2019.

[10] S. E. Pour and R. Javidan, "A new energy aware cluster head selection for LEACH in wireless sensor networks", *IET Wireless Sensor Systems*, Vol. 11, No. 1, pp. 45-53, 2021.

[11] A. A. Baradaran and K. Navi, "HQCA-WSN: High-quality clustering algorithm and optimal cluster head selection using fuzzy logic in wireless sensor networks", *Fuzzy Sets and Systems*, p. 389, 2020.

[12] A. Panchal and R. K. Singh, "Eadcr: energy aware distance-based cluster head selection and routing protocol for wireless sensor networks", *Journal of Circuits, Systems and Computers*, Vol. 30, No. 04, pp. 114-144, 2021.

[13] P. S. Khot and U. Naik, "Particle-water wave optimization for secure routing in wireless sensor network using cluster head selection", *Wireless Personal Communications*, Vol. 119, pp. 2405-2429, 2021.

[14] V. Narayan and A. K. Daniel, "FBCHS: Fuzzy Based Cluster Head Selection Protocol to Enhance Network Lifetime of WSN", *ADCAIJ: Advances in Distributed Computing and Artificial Intelligence Journal*, Vol. 11, No. 3, pp. 285-307, 2022.

[15] M. K. Roberts and P. Ramasamy, "Optimized hybrid routing protocol for energy-aware cluster head selection in wireless sensor networks", *Digital Signal Processing*, Vol. 130, p. 103737, 2022.

[16] R. K. Yadav and R. P. Mahapatra, "Hybrid metaheuristic algorithm for optimal cluster head selection in a wireless sensor network", *Pervasive and Mobile Computing*, Vol. 79, p.

Received: November 4, 2023. Revised: December 1, 2023.

101504, 2022.

[17] G. C. Jagan and P. J. Jayarin, "Wireless sensor network cluster head selection and short routing using energy-efficient Electrostatic discharge algorithm", *Journal of Engineering*, pp.1-10, 2022.

[18] A. Kumar, J. L. Webber, M. A. Haq, K. K. Gola, P. Singh, S. Karupusamy, and M. B. Alazzam, "Optimal cluster head selection for energy efficient wireless sensor network using hybrid competitive swarm optimization and harmony search algorithm", *Sustainable Energy Technologies and Assessments*, Vol. 52, p. 102243, 2022.

[19] P. Kathiroli and K. Selvadurai, "Energy efficient cluster head selection using improved Sparrow Search Algorithm in Wireless Sensor Networks", *Journal of King Saud University-Computer and Information Sciences*, Vol. 34, No. 10, pp. 8564-8575, 2022.

[20] M. R. Reddy, M. L. R. Chandra, P. Venkatramana, and R. Dilli, "Energy-efficient cluster head selection in wireless sensor networks using an improved grey wolf optimization algorithm", *Computers*, Vol. 12, No. 2, p. 35, 2023.