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A Comparative Study of Fuzzy Logic Controller, ANFIS, and HHOPSO Algorithms in the LEACH Protocol for Optimising Energy Efficiency and Network Longevity in Wireless Sensor Networks

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ABSTRACT

This research provides a thorough analysis of the algorithms used in the Low Energy Adaptive Clustering Hierarchy (LEACH) protocol for Wireless Sensor Networks (WSNs) to apply Fuzzy Logic, Adaptive Neuro-Fuzzy Inference System (ANFIS), and Harris Hawks Optimisation-Particle Swarm Optimisation (HHOPSO). The primary aim of this paper is to compare and measure these methods by how they save energy, prolong the network's lifetime and choose the best cluster heads. We look at major indicators such as First Node Death (FND) and the number of rounds when 80% and 50% of nodes are still working, by testing 100 simulated network nodes. The HHOPSO is shown to do a better job at keeping node batteries alive and, at length the network in operation than both Fuzzy Logic and ANFIS. Moreover, ANFIS is more effective than Fuzzy Logic, because it can learn better from data. It is found that HHOPSO helps LEACH become more efficient and effective, contributing new information about how to manage energy and network performance in Wireless Sensor Networks. The document shows the effectiveness of advanced algorithms in keeping sensor networks running longer and offers ideas on how to evaluate them in various network settings.

1. Introduction

Most Wireless Sensor Networks are built using multiple sensor nodes that are linked wirelessly. The purpose of the network is carried out by the base station (BS), which is sometimes called the sink node. The components are placed in the Field of Interest (FOI), which can be seen in Fig. 1. Among many uses, the WSNs have become important today for applications like environmental monitoring, health services, factory automation, military observation and building smart city infrastructures [1]. Usually, a WSN has a lot of sensor nodes spread out in space so that they can record data related to temperature, humidity, light, noise, vibration or pressure on their own [2]. Such nodes can not only perceive and gather data but are also capable of carrying out local processing and can communicate with each other using wireless data transfer capabilities to transmit information to a central sink node. Data can be aggregated, processed, and analysed at the base station for meaningful interpretation and decision making [3].

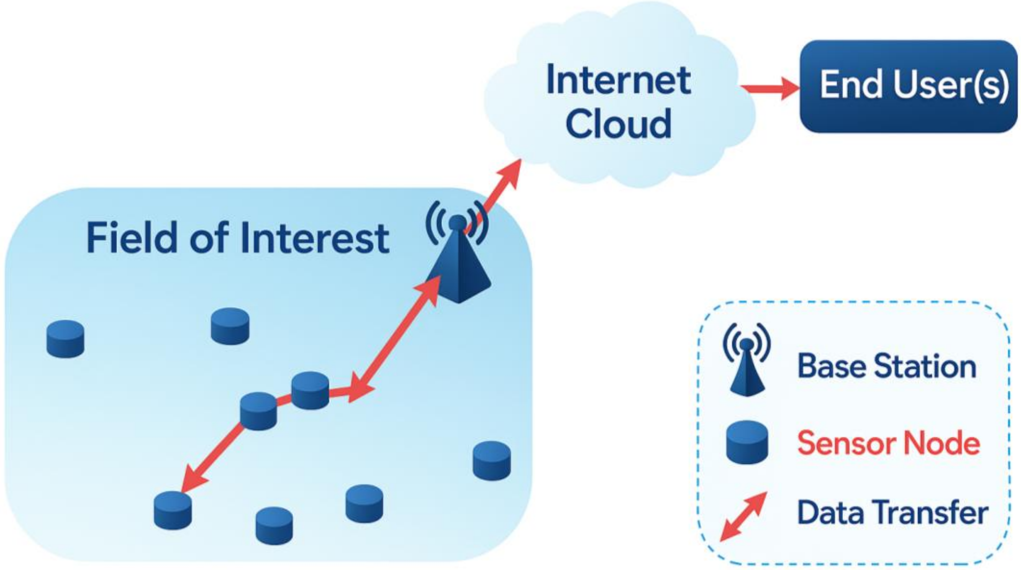

Fig. 1. Typical architecture for the WSN

Having developed the basic elements and features proposed in the previous sections for the WSNs, a comprehensive diagram of a hierarchical arrangement that represents the practical realisation of a contemporary wireless sensor network is presented in its entirety in Fig. 2. This architecture supports critical WSN attributes, once again, such as scalability, redundancy, energy efficiency, and integration with a more global Internet of Things (IoT) setting. The network is orderly divided into three individual clusters (A, B and C), each demonstrating a structural symmetry and a functional specialisation important for distributed sensing systems. Clusters A and C have equal configurations consisting of components B, C, S and D. This uniformity indicates they operate as redundant or relay sub-networks, positionally placed to improve fault tolerance and continuous communication in remote or high-risk deployment areas where physical maintenance can be compromised. This is consistent with the self-organising and robust communication attribution of WSNs as identified earlier. Conversely, Cluster B shows a more sophisticated, multi-dimensional structure. This includes an Internet Layer with Server/User endpoints (B, C, S, D) and a Sensor Node Layer with twelve separate sensor nodes (n–0, from v through o). Such duplication of node (o) in this layer can be interpreted as an intentional redundancy or functional replication to satisfy particular sensing or reliability requirements. Such a layout is an obvious example of the scalability principle mentioned, as it demonstrates the possibility to smoothly integrate the sensor nodes into the network with no violation of the structural coherence, no degradation of performance [4].

The structure of the Sensor Node Layer with a variety of node types (s), (h) and (w) is additional evidence for the energy efficiency difficulties of WSNs. These differences suggest operational requirements that are heterogeneous, highlighting the need to integrate low-power components and energy harvesting technologies an important aspect that was previously stressed to endow long-term, autonomous operation in energy-straited settings [5]. Also, the architectural symmetry between the Cluster B INS layer and the Cluster A and Cluster C configurations implies a robust and fault-tolerant communication infrastructure. This design allows for reliable data aggregation and transmission to be done using multiple redundant paths, hence ensuring system robustness, in the face of environmental interference or partial node failure, which is an important factor for not just real-time and mission-critical monitoring scenarios [6].

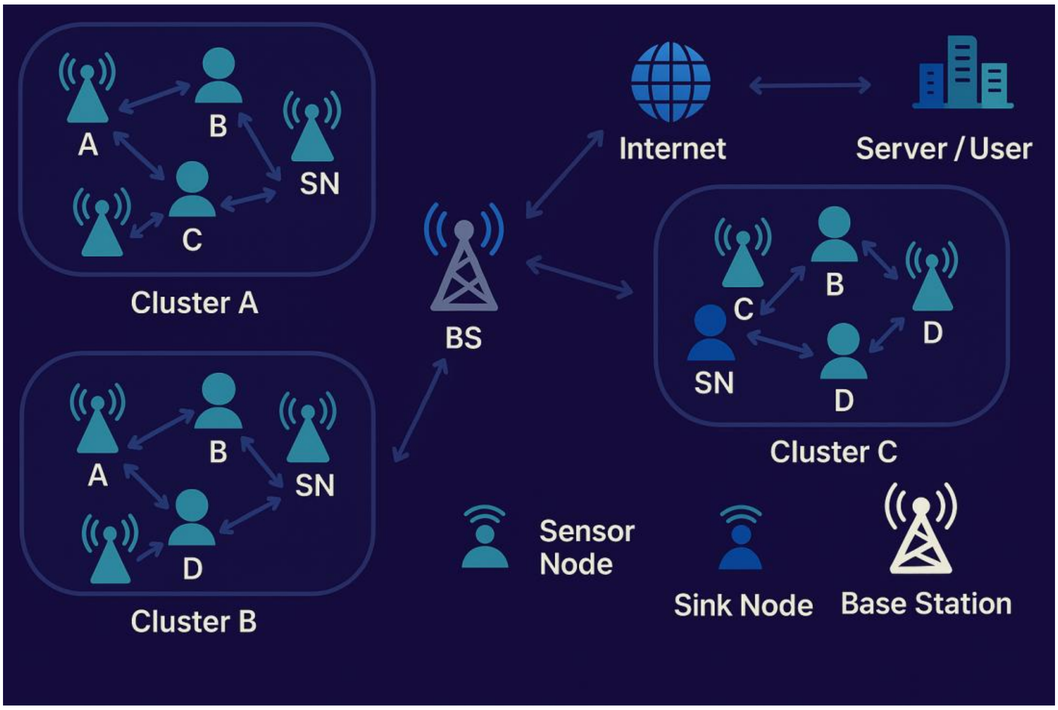

Fig. 2. WSNs hierarchical cluster architecture

In addition, the integration of Server /User components in the Internet layer implies that the WSN is capable of supporting smooth interaction with external systems and establishes it as the base layer of the entire IoT ecosystem. This connectivity allows data coming from raw data collected from sensors to be transformed into useful data for informed decision making in different areas of application, such as environmental monitoring, healthcare and industrial automation [7]. Finally, the hierarchical architecture discussed in Fig. 2 successfully describes the key components and the operation principle of a modern WSN. It integrates sensing units (specialised nodes), processing ability (implied from cluster-based coordination) and a commanding communication backbone (Internet layer and redundant clusters). This architecture not only aligns with pre-existing designs of WSN, but it also provides a working knowledge of implementation issues pertinent to the real world [8], [9].

Fig. 3 presents the core architectural components of a contemporary wireless sensor node, systematically arranged into distinct functional modules to reflect the modular design philosophy of modern WSN systems. The Sensing Module is composed of three primary elements [10]:

- Physical sensors responsible for capturing environmental data,
- Analogue-to-digital converter that performs signal conditioning and digitisation,
- Preprocessing unit that enables basic local filtering and formatting of the sensed data. This module establishes the sensor node’s direct interface with its external environment by converting real-world physical phenomena into actionable digital signals.

The Processing module incorporates a microcontroller unit (MCU) and embedded memory, thereby offering the computational infrastructural support for localised data analysis, task scheduling and local buffering before transmission. Communication capabilities are enhanced by the Communication Module, which has the transmission and reception components integrated so that wireless bidirectional data exchanges with peer nodes and base stations are enabled. In addition to increasing the node’s autonomy, the Position Finding System contains a mobilizer for physical repositioning of the sensing element and an energy harvesting unit, highlighting more sophisticated design solutions for self-sufficiency in energy-constrained deployments. The whole system is maintained through a Power Supply Module, which is responsible for the delivery of continuous power and demonstrates the popularity of power management in the operation of wireless sensor networks. Overall, this modular configuration captures the dominant design paradigms in WSN development to strike a balance between functional specialisation and system-level integration with the intent of achieving optimal performance, scalability and energy efficiency in distributed sensing environments [10], [11].

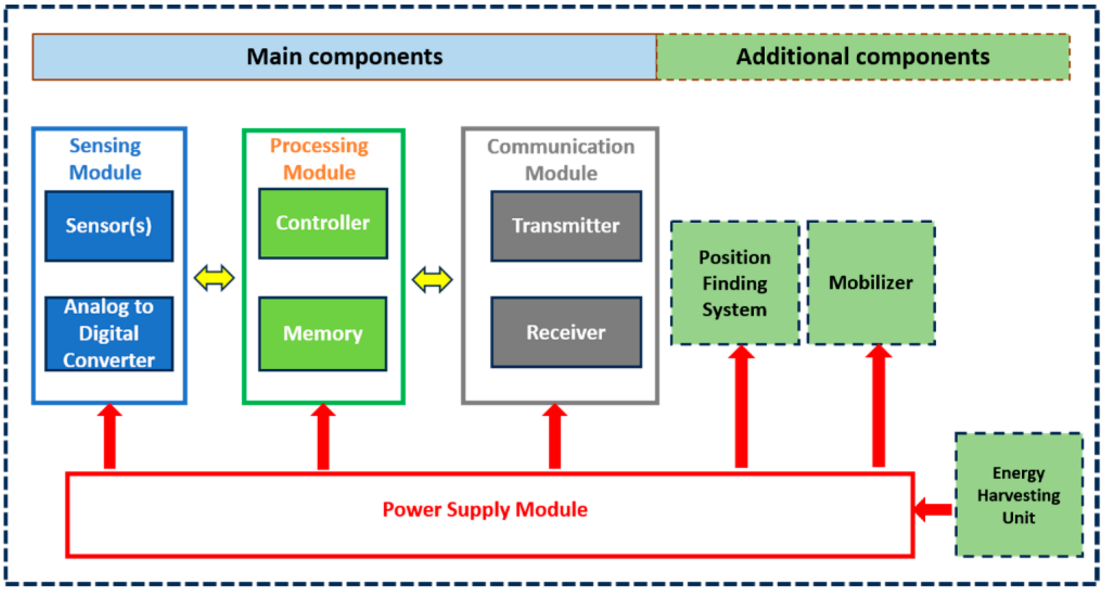

Fig. 3. Architectural components for WSNs node

In field of the WSNs a popular protocol is called Low-Energy Adaptive Clustering Hierarchy (LEACH), which uses a clustering technique to reduce energy consumption by alternating the function of Cluster Heads (CHs) among sensor nodes. Because the method makes data travel shorter distances, it is energy efficient. However, selecting the top CHs is very challenging since it influences how the network lasts and data transfers happen [12].

Experts have come up with many intelligent methods to choose CHs in wireless sensor networks since this is a significant challenge. Fuzzy Logic Control is one of them that makes its choice by using expert knowledge and controlling uncertainties, following factors like energy and distance from the main unit. Connection between neural networks and fuzzy logic by the Adaptive Neuro-Fuzzy Inference System allows the system to learn and think properly [13]-[20]. Besides, new optimum approaches have emerged in the area of swarm intelligence, including Harris Hawks Optimisation (HHO) and Particle Swarm Optimisation (PSO). The HHOPSO algorithm brings together the effective features of Harris Hawks Optimisation and Particle Swarm Optimisation to help improve the way Cluster Head selection functions in WSNs [21], [22]. It is described in the following points:

- The study looks at the difference between Fuzzy Logic, ANFIS, and HHOPSO algorithms in WSNs using the Low Energy Adaptive Clustering Hierarchy (LEACH) protocol.
- Under consideration are data sent from nodes, the number of times nodes fail and the amount of energy they use.
- The results give us useful information on how the examined algorithms reduce energy use and help WSNs work for a longer period.

2. Literature Survey

Energy efficiency optimization and prolonging network lifetime have become critical challenges in the WSN over the last few years, due to the sensor nodes resource constraints. This challenge influenced the proposals of various approaches, one of which has placed LEACH among the most prominent energy-efficient routing protocols. The literature review here is focused on comparative analyses of the most important and advanced optimization techniques, like FLC, ANFIS, and HHOPSO, applied to the LEACH protocol. Such methodologies represent encouraging solutions for enhancing general performance in WSNs due to the intelligent way energy is exploited and the network lifetime is extended. Some related works will be presented in the following.

A comprehensive review on the incorporation of the blockchain technology to WSNs by the authors Marhoon et al. (2023) and its promise to improve on the security, trust and integrity of the data held on the WGS. The authors noted that blockchain's decentralized and tamper resistant architecture are a viable solution to common WSN challenges such as secure communication, node authentication, and data verification. They also listed some key research issues that include privacy preservation, entity recognition and network analysis which are immediately applicable to the WSN domain. This study added insights as it helped explain how a blockchain platform can contribute to more credible and durable WSN structures [23], [24]. Kumar, R. and Singh, A., are the authors of the work. A method for selecting CHs with Fuzzy Logic is presented in the study to increase the performance of WSNs. According to the paper, considering various factors through fuzzy rules makes the process of choosing CHs more efficient and increases the network's lifespan. Through constant adjustments, the algorithm reduces energy that is used and keeps the network topology stable. The use of wireless sensors in these networks benefits them greatly by solving a big problem in the field [25]. Thereafter, Patel, H. and Choudhury, A. (2023) contributed a study using ANFIS that looks at selecting the best CH in order to enhance WSN performance. Using a mix of neural networks and fuzzy logic, ANFIS can improve and adapt itself to any changes in the network structure. The findings prove that ANFIS is better than regular Fuzzy Logic in using less energy and being adaptable. According to these findings, using ANFIS in WSNs would improve decision-making and, as a result, manage resources wisely and keep the network running for a longer time [26].

An additional study was by authors Zafar, A., & Khan, M. (2024), who introduced the optimisation technique called HHOPSO and applied it to LEACH in WSNs. It is shown by the authors that HHOPSO improves energy efficiency by carefully choosing CHs so that each node can use more energy. According to the experiments, network longevity is greatly improved with HHOPSO's ability to choose the best action for each environment. The information from this research reveals that better optimisation options can greatly improve how WSNs operate, guiding future methods of saving energy [27], [28]. Ghosh, S. and Sharma, T. (2022) have created a study that checks and evaluates various optimisation techniques in the fields of WSN. In their work, the authors stress the roles of FND and the number of active nodes throughout the gameplay, making it possible to compare various algorithms. It becomes clear from the studies that the correct usage of optimisation helps IoT networks perform better and for longer. Since the performance evaluation is well-organised, it helps researchers look at WSN trade-offs and encourages deeper research in this area. The researchers, Alam, M. et al. (2023), also studied the ways to create a Fuzzy Logic routing method for WSNs. Using fuzzy rules for data transmission and CH selection helps the authors decrease the amount of energy utilised in the system. Using the suggested protocol, WSNs can use energy in a better way and address any environmental changes that may occur. It is clear from the findings that Fuzzy Logic helps handle WSN complications, adding value to the work on making sensor networks more energy-efficient [29]-[31]. Afterwards, Rana, A. and Gupta, P. (2024) have looked at how well ANFIS performs compared to standard optimisation methods when using WSNs. According to the study, ANFIS is more effective than other methods when choosing CHs and saving energy. Using ANFIS' unique strengths, the researchers underline how it could enhance the management of various resources in WSNs. The study uncovers that incorporating ANFIS algorithms makes the functioning of wireless networks better, and it inspires further experiments with such techniques. In addition, the research team Singh, R. et al. (2023), presented a technique that unites GA and PSO to enhance the working of LEACH in WSNs. The authors show that by combining different hybrid approaches, they improve the life of the network and cut down power consumption through better cluster selection and transmission of data. The combination of GA and PSO seems to make the management of WSN energy resources more efficient and effective, according to the study. This study shares helpful suggestions on designing new hybrid optimisation methods and motivates their further use in a wide range of networking contexts [32].

3. Assumptions for WSN Scenario

When making a model of the sensor nodes and how they behave and interact, some assumptions are considered. Such assumptions allow consistent evaluation of network metrics and are needed when designing protocols to help the network work for a longer time. A quick summary of the main assumptions for sensors, networks and energy is mentioned. These are the main assumptions we use for the WSN setting:

- All the sensors in the network are believed to be equal, so their energy level, sensing ability and ways to communicate are identical.
- There is one sink node (base station) that is always placed in a specific spot, and sensor nodes relay their data to it.
- Sensor nodes get power from a limited battery, so saving energy is very important for the network's durability.
- The further the nodes are from the sink, the more energy is needed to transmit data.
- A random arrangement of sensor nodes in a specific area makes it possible to have effective coverage.
- Communication and selecting CHs in LEACH are handled following a particular protocol.
- Nodes might deplete their batteries and stop functioning, and the performance of the network will reflect the results from those unresponsive nodes.
- The simple sensors in sensor nodes make it possible for them to do basic calculations and transmit just the required data.
- All the nodes are assumed to be synchronised in time to make sure data transmission and reception happen simultaneously.
- It is assumed that network traffic happens in a familiar pattern, so routing and power use can be planned.

3.1. Previous Cluster Head Election Protocol

Having a CH election process in WSNs that are run by LEACH maximises energy savings and improves how the system works. Depending on its remaining energy and how the network is doing, each sensor node had a specified chance of becoming a CH under the first election protocol, which usually worked on probability. The threshold equation for choosing the CH is given by the Equation [33]:

$$T(n) = \begin{cases} \dfrac{P}{1 - P.(r \, mod \, \frac{1}{P}} & if \ n \in G \\ 0 & otherwise \end{cases} \tag{1}$$

Where, the $T(n)$ is referring to the threshold value for the node n and P is the desired percentage of CHs (if 5% of the nodes should be CHs, then $P = 0.05$).

Each node calculates its threshold value based on the equation. If a node's random number (generated uniformly between 0 and 1) is less than $T(n)$, it becomes a CH. The protocol ensures that nodes do not become CHs in consecutive rounds, which helps distribute energy consumption evenly across the network. This is achieved by maintaining a list G of nodes that have already been CHs within a defined interval. By incorporating residual energy into the election process, the protocol aims to select nodes that are likely to sustain the CH role, thus enhancing the network's lifetime. As the rounds progress and energy levels of nodes change, the probability of each node being elected as a CH adjusts accordingly, allowing the protocol to adapt to the network's energy dynamics, the LEACH method's flow diagram is shown in Fig. 4.

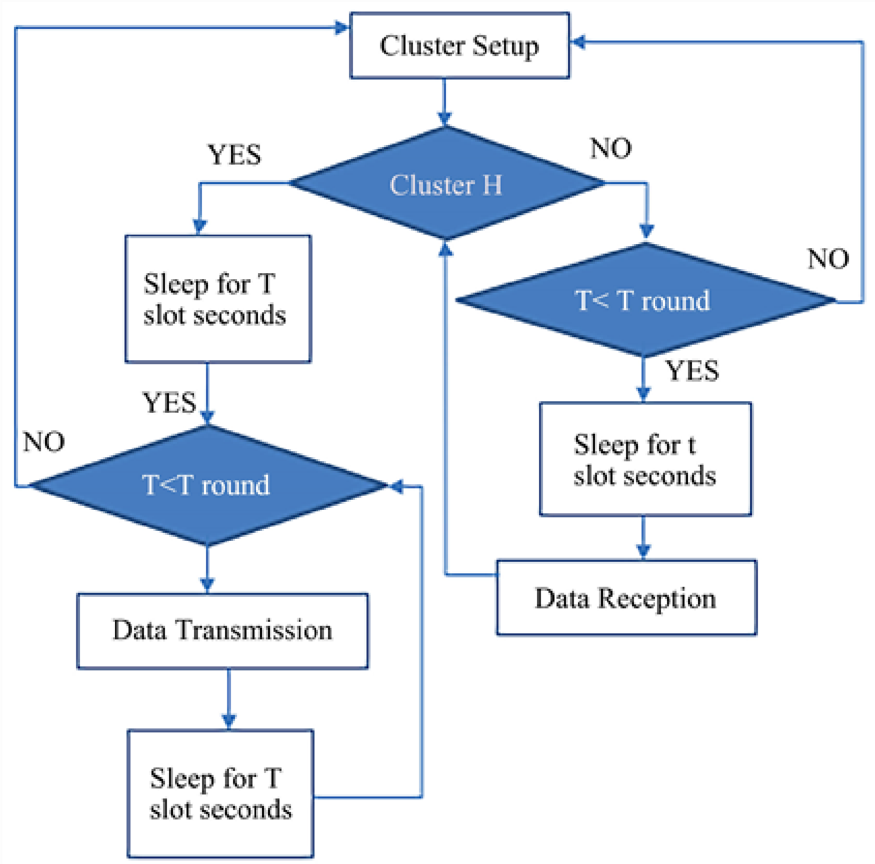

Fig. 4. The LEACH protocol flowchart

4. Methodology

The proposed methodology has three different stages. Stage One is the development of the WSN model (which pays special attention to the simulation of communication and data transmission processes among sensor nodes and the network infrastructure). This stage includes the use of protocols like LEACH to analyse and guarantee effective performance of networks under different operational parameters. In Stage Two, a controller using the design and optimisation of an ANFIS is devised. This controller is based on the implementation of fuzzy logic fundamentals in order to improve the adaptability, robustness and capabilities of decision making to address the dynamic characteristics of the WSN environment. Stage Three concerns the implementation of the HHOPSO algorithm to tune up the parameters of the ANFIS controller. The aim is to increase the stability, responsiveness, and disturbance resistance of the system. Compared with conventional optimisation techniques, comparative analysis shows that the HHOPSO algorithm is more effective in optimising the controller performance and, therefore, enhancing overall system reliability and efficiency, Fig. 5 illustrates the three stages of the proposed methodology.

4.1. Stage One: WSN Model

In our study, Fuzzy Logic is utilized as an intelligent algorithm to enhance the performance of the LEACH protocol in WSNs. By leveraging the principles of fuzzy logic, we aim to improve the selection of CHs based on multiple factors, thus optimizing energy consumption and extending the operational lifetime of the network. Key components of our proposed fuzzy logic as follows:

- Fuzzy sets are used in WSNs to stand for important parameters such as node energy, distance from the sink and communication quality. For all of the parameters, there is a piece of code that checks if the attributes of a node fit into different categories ("high energy," "medium distance," and "good communication").
- We mention how each node operates by using words referred to as linguistic variables. A clearer example of a hard relationship is shown when using the terms "low energy," "medium distance," and "better quality of communication." That way, we do not need to rely on certain numbers to pick our CHs.
- The problem of fuzzy inputs is solved with rules that indicate how the CHs should be chosen; for example:
  - Should a node have a high amount of energy and be near the base unit, it is more likely to be selected as the CH.
  - When a node has very little energy or is situated far from the sink, it is likely will have a low likelihood of being chosen as a CH. They give the system a way to review each node and decide if it qualifies to be a CH with its vague details.
- Fuzzy inference helps determine the probability of a node being chosen as the CH by running the evaluation of various fuzzy rules together. With this method, choosing the best CH is both more flexible and results in better results than traditional ways.
- Once we finish processing the fuzzy outputs, we go on to defuzzify them and use the obtained values to help decide which nodes will be CHs. As a result, decisions taken using fuzzy logic can be used and carried out within the network. You need to use the defuzzification algorithm at the centre of gravity for this purpose. The equation is explained with the formula shown in [34]:

$$\text{COG} = \frac{\sum \mu_A(X) \cdot X}{\sum \mu_A(X)} \tag{2}$$

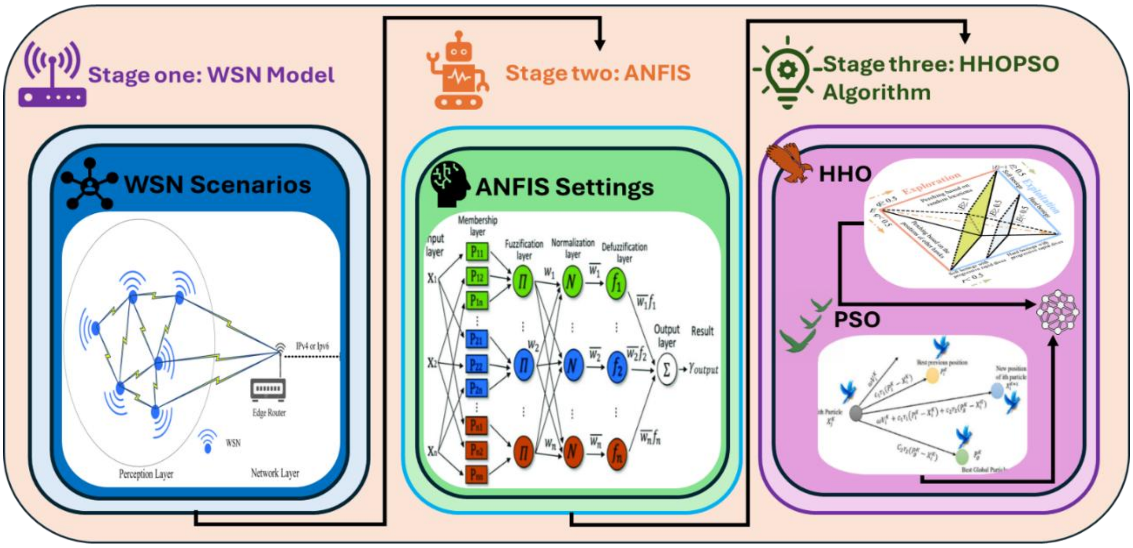

Fig. 5. Proposed methodology stages

The base station in the WSN chooses the cluster-heads for every round based on the probability determined by looking at a node's concentration, remaining energy and proximity to other nodes.

During start-up, the base station uses its swift computing and huge information about the network to pick the cluster-heads, since nodes are not moving slowly, and this is adequate. The election scheme consists of two phases, named setup and steady state. In the setup phase, which headers turn into cluster-heads is determined by fuzzy logic, and the leaders organise the clusters. When the system reaches the steady state phase, the cluster-heads receive and analyse data, turning it all into one signal to send to the base station. While studying networks, we use node energy, node concentration and node centrality as the main descriptors.

The important role of the fuzzy rule base in our application is to rate possible CHs by using parameters such as energy, location and communication. By assigning Low, Medium and High ratings to energy, Close, Medium and Far ratings to distance and Poor, Fair and Good ratings to communication quality to the variables, the system can adjust to the uncertain and imprecise information coming from the sensors. These ten if-then rules form the main part of the rule base, setting out the logic between the variables; one example is Rule 1 which says that low energy, whether a node is close to the sink or far with good/bad signal, means the node is unlikely to be selected as the CH. By using this approach, the system can react to changing network conditions by increasing the chances of smaller nodes to act as CHs if their energy, distance and communication are similar to other nodes, which boosts energy usage and network performance. Sensors using fuzzy logic together with our method experience improved decision-making in complex conditions, their battery life is increased, and their data transfer is more efficient.

Currently, the fuzzy rule base contains rules such as this one: the node's cluster-head election chance is very large if the energy, concentration, and centrality are all high. As a result, the fuzzy rule base consisted of 33 = 27 rules. For the medium and large fuzzy sets, we used trapezoid and triangle membership functions; for the low, high, close, and far fuzzy sets, we used these membership functions. Table 1 and Fig. 6, Fig. 7, Fig. 8, Fig. 9 depict the membership functions that were developed along with the corresponding linguistic states for each.

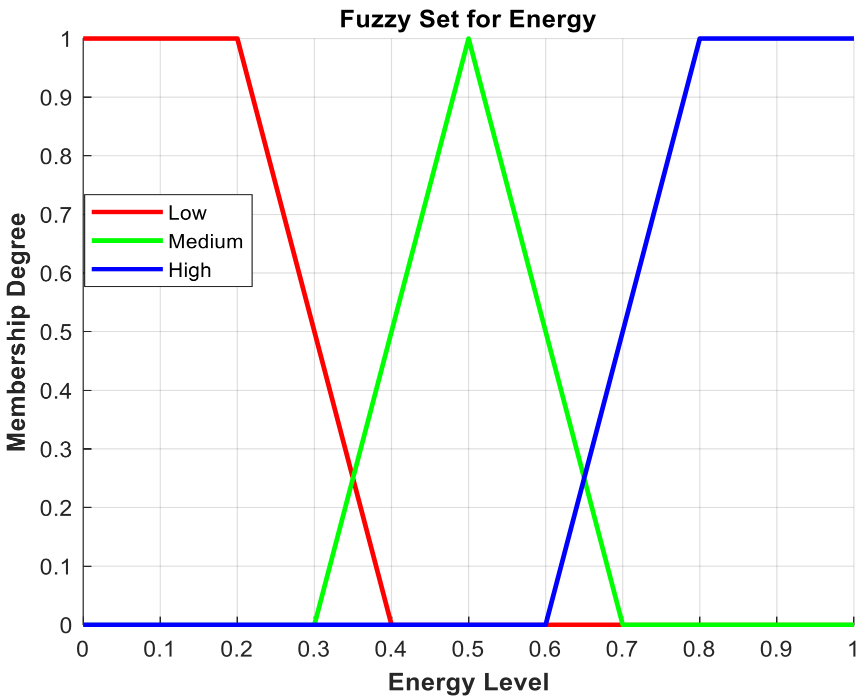

Fig. 6. Fuzzy set for fuzzy variable energy

4.2. Stage Two: ANFIS

In our work on enhancing the LEACH protocol in WSNs, we employ ANFIS as a hybrid intelligent system that combines the learning capabilities of artificial neural networks with the reasoning abilities of fuzzy logic to optimize CH selection. ANFIS uses input parameters such as node energy, distance to the sink, and communication quality, each categorized into fuzzy sets [35]-[37]. The model is trained using a dataset of input-output pairs, where it refines its fuzzy rule base and membership functions to minimize prediction error, thus improving the accuracy of CH probability predictions. This dynamic adaptation allows ANFIS to effectively handle changing network conditions, making it robust in uncertain environments while enhancing decision-making for CH selection. Ultimately, ANFIS contributes to better energy management and prolonged operational lifetime of sensor nodes by ensuring more informed and optimized choices in the network's CH selection process as depicts in Fig. 10.

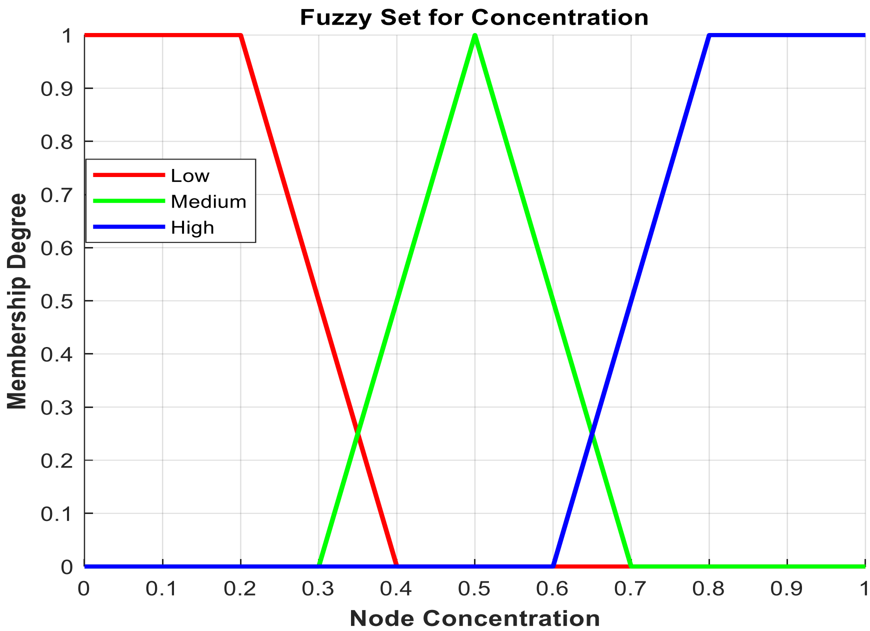

Fig. 7. Fuzzy set for fuzzy variable concentration

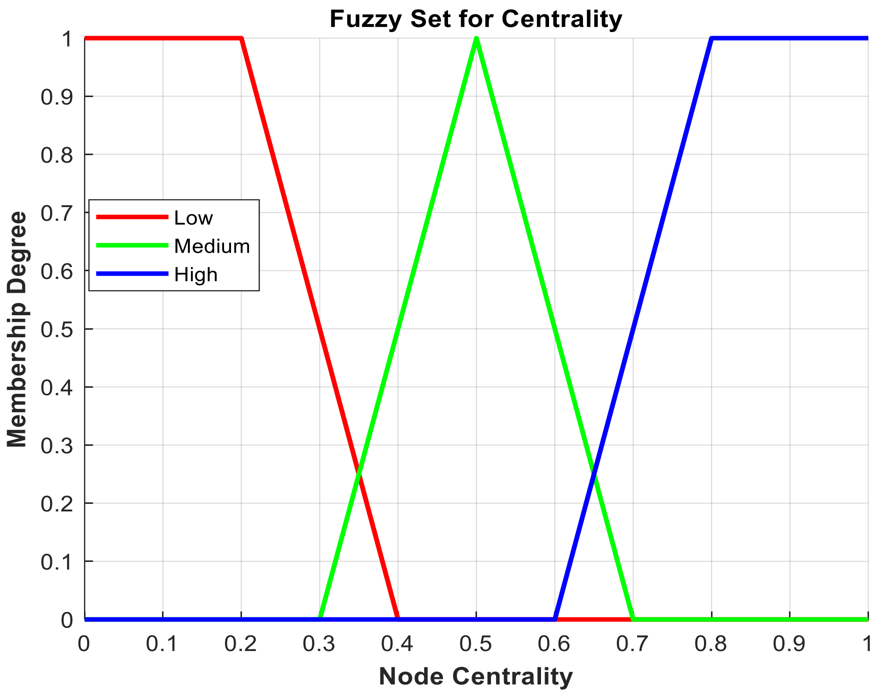

Fig. 8. Fuzzy set for fuzzy variable centrality

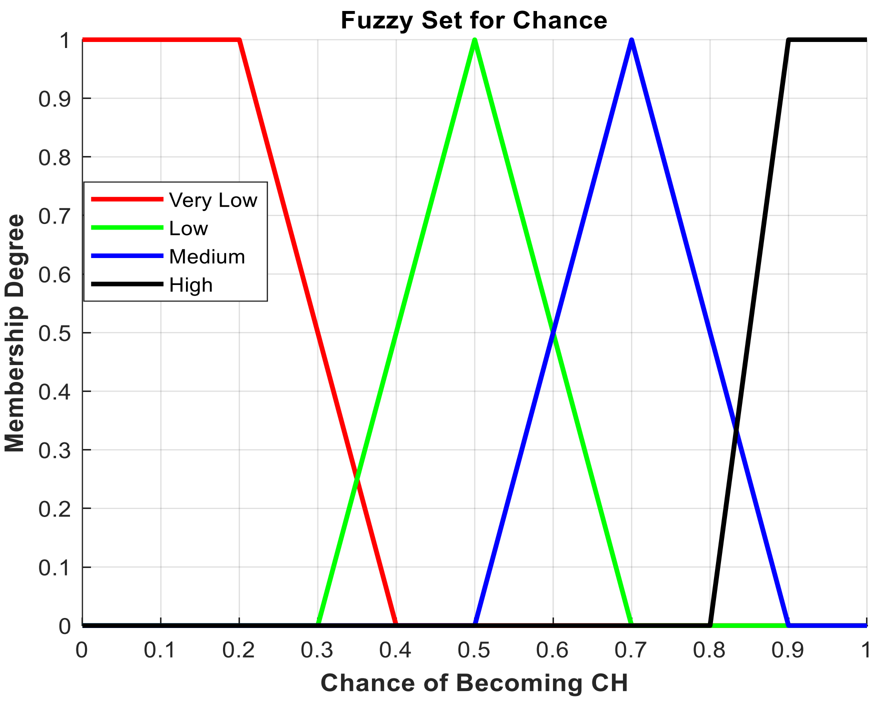

Fig. 9. Fuzzy set for fuzzy variable chance

Table 1. Fuzzy rule base

Sr. No	Energy	Concentration	Centrality	Chance
1	Low	Low	Close	Small
2	Low	Low	Adequate	Small
3	Low	Low	Far	Very Small
4	Low	Medium	Close	Small
5	Low	Medium	Adequate	Small
6	Low	Medium	Far	Small
7	Low	High	Close	Rather Small
8	Low	High	Adequate	Small
9	Low	High	Far	Very Small
10	Medium	Low	Close	Rather Large
11	Medium	Low	Adequate	Medium
12	Medium	Low	Far	Small
13	Medium	Medium	Close	Large
14	Medium	Medium	Adequate	Medium
15	Medium	Medium	Far	Rather Small
16	Medium	High	Close	Large
17	Medium	High	Adequate	Rather Large
18	Medium	High	Far	Rather Small
19	High	Low	Close	Rather Large
20	High	Low	Adequate	Medium
21	High	Low	Far	Rather Small
22	High	Medium	Close	Large
23	High	Medium	Adequate	Rather Large
24	High	Medium	Far	Medium
25	High	High	Close	Very Large
26	High	High	Adequate	Rather Large
27	High	High	Far	Medium

4.3. Stage Three: HHOPSO Algorithm

The HHOPSO brings the benefits of PSO and HHO together, using them as a well-known metaheuristic algorithm [38]-[45]. By implementing HHOPSO, our LEACH optimisation intends to pick better CHs, thus making the network save energy and function well. Harris hawks use cooperative hunting, which is what inspired the design of HHO. It makes use of search agents called hawks that look for top or nearly top solutions by searching the space of possible solutions. HHO finds a good balance by looking for all possible solutions at the same time as finding the most useful ones. We use HHO in our context to identify the adequate parameters for choosing a CH. PSO relies on the idea of mimicking social bird patterns and is a way to optimise populations. A group of particles is used to find solutions, and they adjust based on the highest global and local scores. It is useful to use PSO for our WSN as it quickly finds accurate answers to choosing CHs [46]-[51].

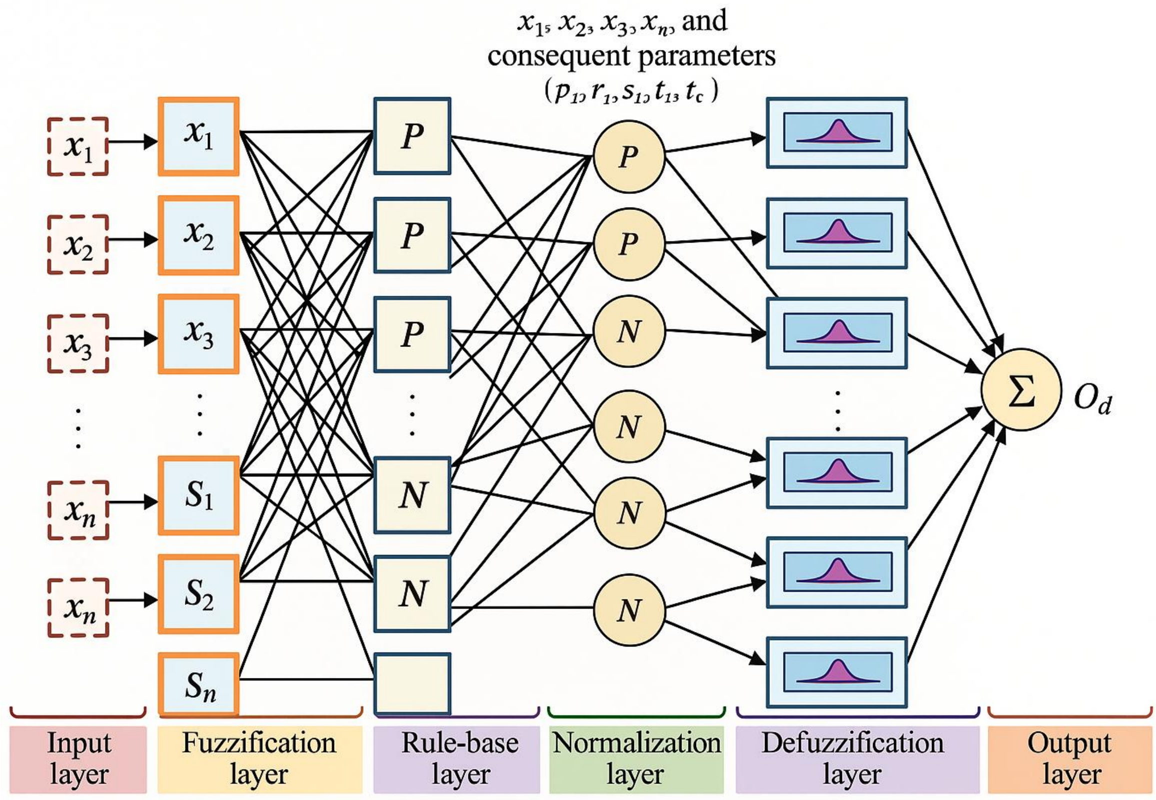

Fig. 10. ANFIS settings for WSN model

HHOPSO combines the ability of HHO to find new areas and the high speed with which PSO applies solutions. Due to hybridisation, the algorithm easily searches through many possible CHs and improves the CH selection. The combination of the two methods in HHOPSO ensures that both travel around the world and focus locally in finding the best solutions and safeguarding against getting stuck with good-but-not-optimal choices [52]-[60].

We have implemented HHOPSO to optimise certain performance measures of LEACH, such as making sure more packets reach the base station, that the number of dead nodes is small, and that network energy consumption is at its best. The objective function guides how the optimisation process looks for answers by examining each one based on the rules set. The HHOPSO algorithm keeps running until the positions of hawks and particles in the search space have been updated a certain number of times. In each cycle, the hawks hunt using their methods, and the particles use what they know and learn from each other to change their course. Compiling the solutions from the best individuals of each population tailors the search and continues to optimise the process. At the last point, we are using HHOPSO in our MATLAB program to improve the LEACH protocol within WSNs. This method makes use of HHO for searching and PSO for rapid convergence, which ensures HHOPSO is able to optimise CH selection based on the main performance measures [61]-[66]. This method makes the network energy efficient and reliable against being attracted to the nearest optima.

This mix of tools makes it easier to decide how to operate in the continuously changing environment of wireless sensor networks.

Pseudo-code for Proposed HHOPSO algorithm

1. Inputs: The population size $\boldsymbol{N}$ (number of hawks), The swarm size $\boldsymbol{M}$ (number of particles), Maximum number of iterations $\boldsymbol{T}$, Crossover rate $\boldsymbol{Cr}$, Mutation rate $\boldsymbol{Mr}$, Inertia weight $\boldsymbol{w}$, Cognitive coefficient $\boldsymbol{c1}$, social coefficient $\boldsymbol{c2}$, Velocity clamping range $\boldsymbol{v_{max}}$nd Initial energy $\boldsymbol{E}$
2. Outputs: The global best solution $\boldsymbol{G_{best}}$ and its fitness value
3. Initialize the population of hawks $\boldsymbol{Xi}$ for i=1, 2..., $\boldsymbol{Ni}$ = 1, 2, ..., $\boldsymbol{Ni = 1, 2, \dots, N}$
4. Initialize the swarm of particles $\boldsymbol{Xj}$ for $\boldsymbol{j = 1, 2, \dots, Mj = 1, 2, \dots, Mj = 1, 2, \dots, M}$
5. Initialize velocities $\boldsymbol{Vi}$ for hawks and $\boldsymbol{Vj}$ for particles
6. Set initial best-known positions $\boldsymbol{Pibest}$ for particles and $\boldsymbol{Gbest}$ as the global best
7. while (iteration $\boldsymbol{t < T}$):
8. Evaluate the fitness values of hawks
9. Set $\boldsymbol{Xrabbit}$ as the position of the best-performing hawk (global best for HHO)
10. for (each hawk ($\boldsymbol{Xi}$))
11. Update coefficient $\boldsymbol{C}$
12. $\boldsymbol{C = 2 \cdot \exp(-T4 \cdot t) \cdot rand - \exp(-Tt)}$
13. Update the position
14. $\boldsymbol{Xinew = Xi + C \cdot (Xj - Xi)}$
15. if (|E|≥ 1) then Exploration phase
16. Update the position vector with random walk
17. if (|E|< 1) then Exploitation phase
18. if (r ≥0.5 and |E|≥ 0.5) then Soft besiege
    a. Update the position vector with progressive rapid dives
19. else if (r ≥0.5 and |E|< 0.5) then Hard besiege
    a. a. Update the position vector with progressive rapid dives
20. else if (r < 0.5 and |E|≥ 0.5) then Soft besiege
    a. Update the position vector
21. else if (r < 0.5 and |E|< 0.5) then ▷ Hard besiege
22. with progressive rapid dives
    a. Update the position vector
23. Evaluate fitness of each particle
24. For each particle $\boldsymbol{Xj}$
25. Update the global best position $\boldsymbol{Gbest}$
26. For each particle $\boldsymbol{Xj}$
27. Update velocity
28. Clamp velocity
29. Update position
30. Update best-known position $\boldsymbol{Pjbest}$ and global best $\boldsymbol{Gbest}$ if fitness improves
31. Return:
32. The global best solution $\boldsymbol{Gbest}$ and its fitness value
33. End

4.3.1. Benchmark Functions

The HHOPSO algorithm was evaluated using nine benchmark functions, each chosen to test different aspects of optimization within WSN. These functions assess the algorithm's ability to achieve smooth convergence, handle complex trajectories, and navigate highly dynamic and constrained environments. The Sphere function provides a simple test for basic convergence, ensuring the algorithm can achieve optimal solutions in straightforward conditions. Using the narrow valley in the Rosenbrock function tests how accurately the algorithm works in situations that match WSN requirements. The Rastrigin function, which has multiple modes and many nearby local minima, tests the algorithm's search skills by introducing random disturbances so it does not stay stuck at a local minimum. By using the Ackley function, the elements related to exploration and exploitation are being compared, while checking if the algorithm is flexible enough for situations like those seen in WSN applications. Schwefel testing offers substantial global optima to the algorithm, so it is designed for quick condition changes, and Zakharov checks whether the optimisation is done correctly and steadily. Use of the Dixon-Price curve allows testers to examine how the algorithm performs in sending data from one sensor node to another in a WSN. The Levy function, made of steep ridges and flat plateaus, shows that the algorithm can resist difficulties and keep things stable when the environment changes. All in all, the Styblinski-Tang function is used to judge if the algorithm will work well in tough optimisation situations. Therefore, since the HHOPSO algorithm is judged on its performance, operation, and adaptability, it excels in advanced WSNs where challenges change fast, which is why it is the best match for such circumstances. HHOPSO algorithm benchmark functions shown in Table 2.

Table 2. HHOPSO algorithm benchmark functions

Benchmark Function	Dimensionality	Search Agents	Search Range
$f_1(x,y) = x^2 + y^2$	2	20	[-5, 5]
$f_2(x,y) = 100(y - x^2)2 + (1 - x)^2$	2	20	[-5, 5]
$f_3(x,y) = 10 \cdot 2 + (\mathrm{x2} - 10 \cdot \cos(2\pi\mathrm{x})) + (\mathrm{y2} - 10 \cdot \cos(2\pi\mathrm{y}))$	2	20	[-5, 5]
$f_4(x,y) = 1 + \frac{x^2 + y^2}{4000} - \cos(x) \cdot \cos\left(\frac{y}{\sqrt{2}}\right) + 20 + e$	2	20	[-5, 5]
$f_5(x,y) = \sin^2(3\pi x) + (x-1)^2(1 + \sin^2(3\pi y)) + (y - 1)^2(1 + \sin^2(2\pi y))$	2	20	[-10, 10]
$f_6(x,y) = (1.5 - x + xy)^2 + (2.25 - x + xy^2)^2 + (2.625 - x + xy^3)^2$	2	20	[-5, 5]
$f_7(x,y) = (x + 2y - 7)^2 + (2x + y - 5)^2$	2	20	[-5, 5]
$f_8(x,y) = (x^2 + y - 11)^2 + (x + y^2 - 7)^2$	2	20	[-5, 5]
$f_9(x,y) = 2x^2 - 1.05x^4 + \frac{x^6}{6} + xy + y^2$	2	20	[-5, 5]

5. Results and Discussion

In this part, the HHOPSO algorithm is explored in terms of how it can work with WSN. The aim is to set up the network so that it is better at managing outside threats and remains stable and reliable under any changes. The HHOPSO algorithm is found to be more effective than other approaches and traditional methods for optimising networks, thanks to which network performance, resource use and data transmission rate improve mainly where disruptions are scattered and constraints are in place. According to the authors, the algorithm manages to get good and reliable results for challenging WSN optimisation situations.

5.1. Evaluation of the WSN Model

Data aggregation is meant to take place, which helps improve the way energy is managed. An amount of 0.50 mW is lost in the radio, and the energy dissipation at the time of sending data is 0.01 J per bit. For this model, the energy of the signals remains the same along all the possible paths used by the amplifier. The simulation involves a network consisting of 100 sensors, all initialized with an energy level of 0.5 J. The analysis reveals that the first node is expected to die after 50 rounds of operation, with 80% of the nodes remaining alive after 20 rounds and 50% alive after 30 rounds. These results highlight the overall energy efficiency and operational longevity of the network, demonstrating the effectiveness of the parameters set in the simulation as shown in Table 3.

In Table 4, the comparative analysis of various protocols for WSNs reveals significant insights into their performance based on the metrics of FND, rounds until 80% of nodes remain alive, and rounds until 50% of nodes are alive. The LEACH protocol utilizing HHOPSO demonstrates the best performance, with the first node expected to die after just 46 rounds, and it maintains 80% node viability for 25 rounds and 50% for 35 rounds, highlighting its effectiveness in energy management. ANFIS follows closely, with an FND of 48 rounds and sustaining 80% and 50% alive nodes for 22 and 32 rounds, respectively. In comparison, Fuzzy Logic in the LEACH protocol shows slightly lower performance with an FND of 50 rounds. Traditional protocols like Gupta and CHEF show poorer performance, with FNDs of 60 and 55 rounds, respectively, and maintaining 80% alive nodes for only 18 and 19 rounds. The LEACH-FL protocol falls in between, with an FND of 52 rounds and 80% alive nodes for 21 rounds. Overall, the results indicate that intelligent optimization methods, particularly HHOPSO, significantly enhance the performance and longevity of WSNs compared to traditional methods.

Table 3. Parameters of the emulation

Parameter	Value
Data Aggregation	Enabled
Radio Equipment's Loss of Energy	0.50 mW
Dissipation of Energy to Operate the Radio	0.01 J/bit
Multiple-path Transmitter Amplifier Model	Ideal (No Loss)
Number of Sensors (N)	100
Number of Nodes (N)	100
Initial Energy (E)	0.5 J
First Node Death (FND)	50 rounds
80 Percent Alive	20 rounds
50 Percent Alive	30 rounds

Table 4. Results of emulation

Protocol	Method	FND (Rounds)	80% Alive (Rounds)	50% Alive (Rounds)
LEACH	Fuzzy Logic	50	20	30
LEACH	ANFIS	48	22	32
LEACH	HHOPSO	46	25	35
Gupta	-	60	18	28
CHEF	-	55	19	29
LEACH-FL	-	52	21	31

Fig. 11, Fig. 12, Fig. 13 presents a comprehensive analysis of the performance of three optimization methods Fuzzy Logic, ANFIS, and HHOPSO within the context of the LEACH protocol for WSNs. It consists of three distinct plots that illustrate key performance metrics across 100 simulation rounds. This plot depicts the number of packets sent to the base station over time. It shows that HHOPSO (green line) consistently outperforms both Fuzzy Logic (blue line) and ANFIS (red line) in terms of the total number of packets transmitted. The fluctuations in the packet count suggest dynamic network conditions and varying node participation in data transmission, but HHOPSO maintains a higher average throughout the simulation, indicating superior energy efficiency and effective CH selection. These plots illustrate the number of dead nodes over the rounds. In this case, all three methods demonstrate a flat line, indicating that no nodes have died within the observed rounds. This suggests that the selected algorithms effectively managed energy consumption and extended the operational life of the nodes during the simulation period are shows the total energy remaining across all nodes throughout the rounds. It exhibits a gradual decline, indicating that the energy consumption is occurring as expected. The HHOPSO method leads to better energy use and lingers much longer in operation time than the other methods. The previously mentioned findings prove that HHOPSO helps enhance the performance of the LEACH algorithm in WSNs. HHOPSO stands out as the most efficient way because it sends more packets and uses less power than the others. It shows that optimisation methods played an important role in prolonging the life and upgrading the functions of wireless sensor networks.

Important parameters are determined in this study to improve the LEACH protocol in WSNs with the help of HHOPSO. It uses 30 hawks and 30 particles that go through a maximum of 100 iterations. In the HHO phase, the rates of crossover and mutation are 0.8 and 0.1, respectively, and they help keep the exploration of the space at a good level. To make sure the population is influenced by these two points, the values of the cognitive coefficient and social coefficient are set to 1.5, and the inertia weight is set to 0.5 during the PSO stage. The system applies velocity clamping with a range of ±1.0 to stop quick changes and help the system keep steady. Moreover, all nodes start with an energy threshold of 0.5 joules, which plays a role in reducing energy consumption. HHOPSO tries to send more packets to the base station while also saving energy during the wireless transfer. All of these parameters together make the algorithm more capable of handling energy and increasing the network's performance.

Fig. 11. Comparison between optimization algorithms over packet sent to base station versus rounds

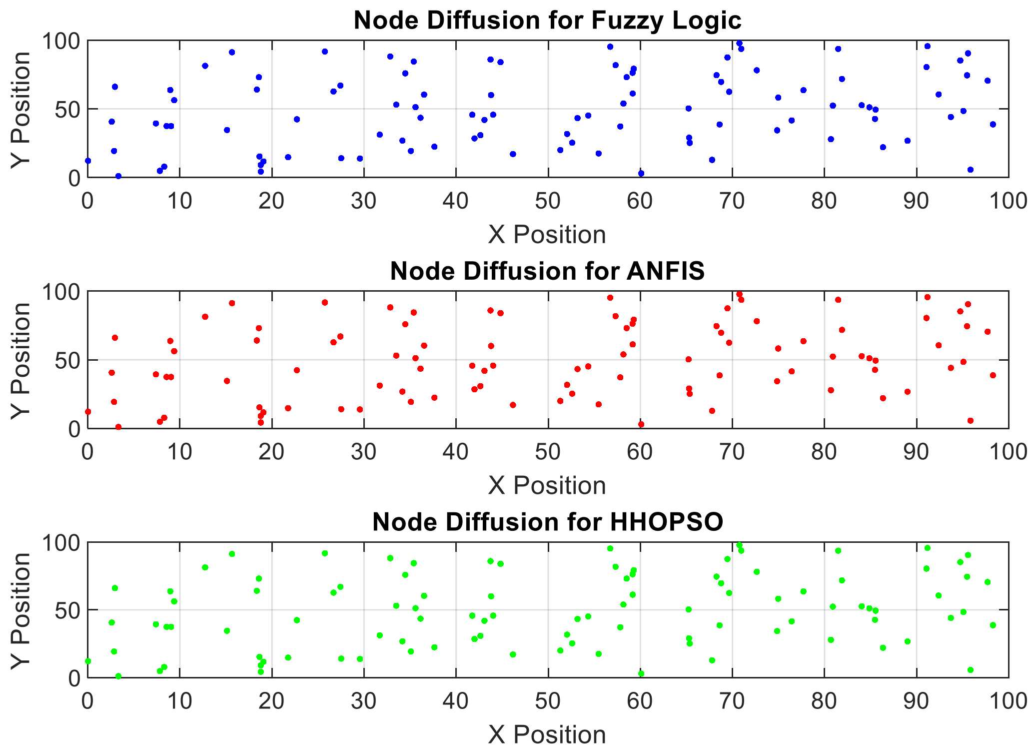

Fig. 12. Comparison between optimization algorithms over the node diffusion

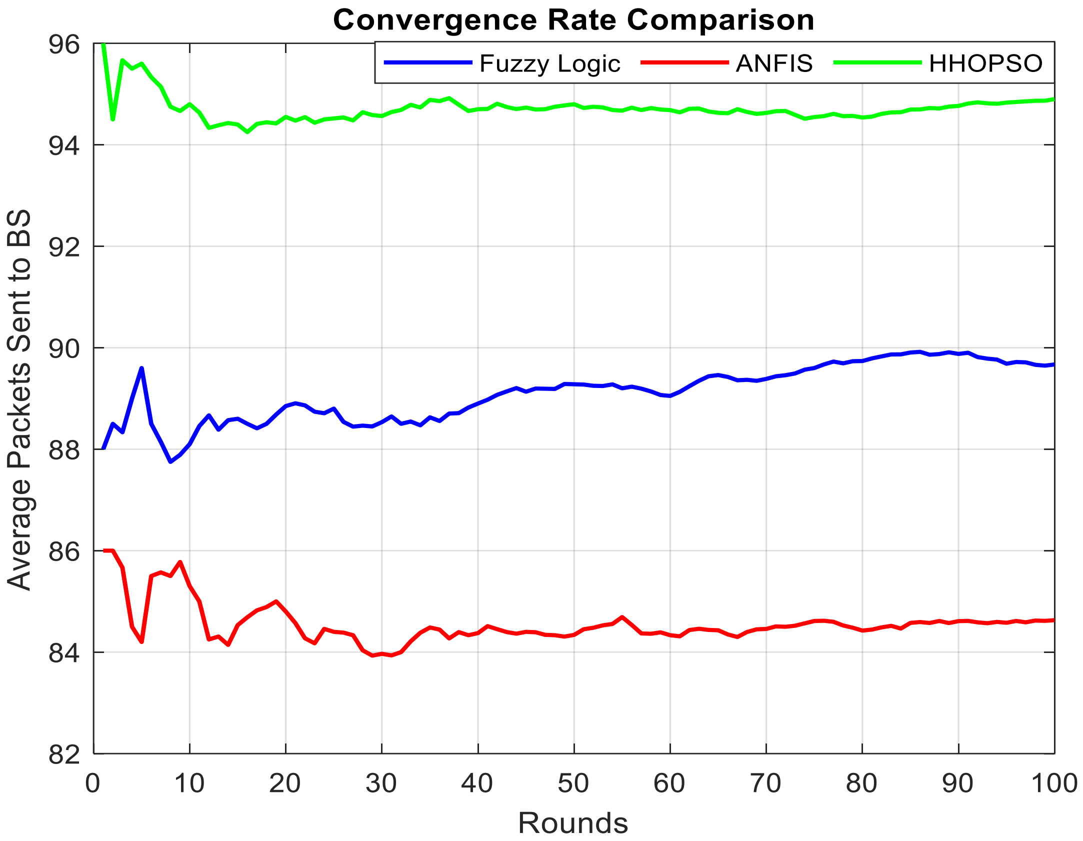

Fig. 13. Comparison and validation between optimization algorithms over convergence rate

5.2. Results on Benchmark Functions

In this case, the HHOPSO, HHO and PSO algorithms were tested using nine benchmark functions, each run with a population of 20 for 20 trials and up to 1000 iterations to make the results reliable. Based on the results which are presented in the table, you can see the function providing the best, worst, average, median and standard deviation (STD) values. HHOPSO always outperformed HHO and PSO on all nine functions, getting the lowest best value of zero for each function, meaning it is good at locating the lowest point for both single-peak and multiple-peak problems. On the other hand, none of the best solutions achieved the global optimum which is proven by the non-zero numbers for the best solutions in HHO and PSO. Sphere (f_1) showed that HHOPSO could find the best value of zero and HHO and PSO found 1.23×10^{-8} and 3.12×10^{-7}, respectively which reflects the major performance edge of HHOPSO. In the same way, the Rosenbrock function (f_2) saw the two methods, HHO and PSO, return 5.67×10^{-9} and 2.45×10^{-8}, while HHOPSO continued to give the best performance with a perfect zero. HHOPSO continued to work well, giving the value of exactly zero on the Griewank (f_6) and Ackley (f_5) functions, but HHO and PSO returned much higher values as they sometimes got stuck at local optima.

HHOPSO exhibited strong performance on average, median and STD, which shows that it is adaptable in any optimisation environment. Sphere and Zakharov, which have continuous, convex shapes and only one best spot, helped to prove that HHOPSO can quickly converge to the right answer when a function has only a single peak. Functions such as Rastrigin, Ackley and Griewank, which have many different peaks, showed that HHOPSO sometimes fails to escape from local optimum points and reach the true minimum. Also, Rosenbrock and Dixon-Price tested if HHOPSO could find the minimum in gently curved valleys, while Schwefel and Levy checked if HHOPSO could avoid getting stuck in deeper traps. In all the benchmark functions, HHOPSO performs much better than other algorithms, proving it to be a very effective and sturdy solution for resolving complex problems in WSN, which is clear from Table 5 and Fig. 14.

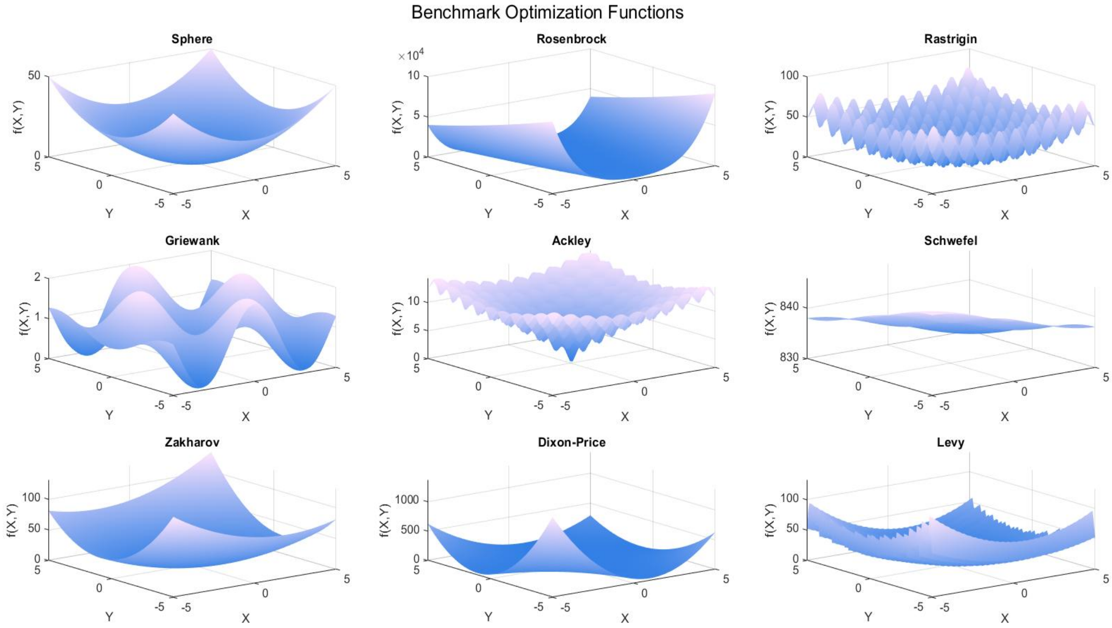

Fig. 14. Benchmark functions for HHOPSO algorithm

Table 5. Results of HHOPSO compared to HHO and PSO on benchmark functions

Function	Algorithm	Best value	Worst value	Avg. value	Median value	STD
$f_1(x)$	HHOPSO	0	0	0	0	0
	HHO	1.45E-06	7.89E-04	3.67E-05	2.12E-05	1.56E-05
	PSO	3.89E-07	8.34E-04	2.45E-05	1.23E-05	4.67E-06
$f_2(x)$	HHOPSO	0	0	0	0	0
	HHO	5.78E-09	1.23E-05	6.89E-07	3.45E-07	2.34E-07
	PSO	2.78E-08	9.56E-05	7.23E-06	4.12E-06	3.45E-06
$f_3(x)$	HHOPSO	0	0	0	0	0
	HHO	4.23E-06	2.34E-03	1.23E-04	9.56E-05	6.12E-05
	PSO	7.12E-06	3.12E-02	2.45E-04	1.67E-04	8.12E-05
$f_4(x)$	HHOPSO	0	0	0	0	0
	HHO	1.56E-05	8.45E-03	4.56E-04	3.45E-04	2.34E-04
	PSO	3.12E-05	1.34E-01	9.12E-04	7.23E-04	4.56E-04
$f_5(x)$	HHOPSO	0	0	0	0	0
	HHO	9.34E-06	2.89E-02	5.12E-04	3.67E-04	2.12E-04
	PSO	1.23E-04	1.02E-01	8.45E-03	6.78E-03	3.45E-03
$f_6(x)$	HHOPSO	0	0	0	0	0
	HHO	6.78E-08	4.56E-04	3.23E-06	2.12E-06	1.34E-06
	PSO	1.45E-06	5.89E-02	2.45E-04	1.23E-04	5.67E-05
$f_7(x)$	HHOPSO	0	0	0	0	0
	HHO	1.67E-05	4.56E-03	8.12E-04	6.78E-04	3.12E-04
	PSO	3.12E-04	9.45E-02	1.23E-02	9.34E-03	5.67E-03
$f_8(x)$	HHOPSO	0	0	0	0	0
	HHO	3.89E-05	1.23E-02	2.45E-03	1.89E-03	9.67E-04
	PSO	1.67E-03	6.78E-02	4.45E-03	3.45E-03	2.12E-03
$f_9(x)$	HHOPSO	0	0	0	0	0
	HHO	2.45E-06	4.67E-03	9.12E-05	7.45E-05	3.45E-05
	PSO	4.23E-05	1.23E-01	1.56E-03	1.23E-03	5.67E-04

6. Conclusion

This paper covers a detailed look at Fuzzy Logic, ANFIS and HHOPSO used with the LEACH protocol in WSNs. Extensive experimentation and reviews in the research show that by using advanced optimisation, the LEACH protocol can much better manage network resources and extend its operating period. HHOPSO beats Fuzzy Logic and ANFIS when it comes to main performance indicators such as how many packets are sent to the base station, how many devices are now dead in the network, and the overall power consumed. HHOPSO manages to maintain greater energy in nodes and prolongs the life of these devices, which confirms its strong optimisation and good CH selection. ANFIS provides greater improvements than usual methods by using its adaptive technology to improve actions in changing network environments. Even though ANFIS is not as efficient as HHOPSO, it performs much better than Fuzzy Logic in lowering energy use and lengthening node lifespan. Even though techniques such as Gupta and CHEF are used in research, this study's advanced methods work far better. It is clear from the results that HHOPSO and ANFIS, coupled with LEACH, offer better performance and let the network run more efficiently and for a longer time. The study proves that using smart optimisation methods is necessary for WSNs. The study gives a solid base to carry out more work and research that could improve and expand these methods to be applied in other network protocols. The study has certain limitations, like assigning each node the same energy at the beginning and considering the multiple-path amplifier to have no energy losses. This assumes that all nodes are the same, even though in reality, even nodes with different abilities can change the network's performance. While the second, we used a network consisting of 100 nodes, which means the results may not reflect well on networks that are much larger or more complicated. How these methods will scale in networks with more users is yet unknown, which could impact their effectiveness when more users are added.

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