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Dynamic Palm Tree Architecture for Energy-Efficient Data Aggregation Using Sugeno Fuzzy Inference System

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ABSTRACT

Traditional data aggregation methods often result in excessive energy consumption, increased aggregation time, and inefficient node selection, limiting their applicability in large-scale UWSNs. The existing approach suffers from redundancy in data aggregation, suboptimal selection of master and local centres, and unbalanced energy utilization, leading to reduced network lifetime. To address these challenges, this work introduced an improved data aggregation scheme based on a palm tree-inspired hierarchical architecture, incorporating fuzzy logic for dynamic node selection. The OPT-FIS utilized a multi-criteria fuzzy logic-based decision-making system to optimize the selection of local centres, considering parameters such as leaflet angle, residual energy, distance to the master node, and energy-to-distance ratio. Fuzzy inference rules, which evaluate the inputs, were created to determine node suitability for local centre selection. The performance of the developed OPT-FIS was evaluated against the existing method using performance metrics of aggregation energy, aggregation time, aggregation ratio, network lifetime, and selection efficiency for master and local centres. The results of the implementation across various communication ranges of 400m, 500m, and 600m showed that the OPT-FIS improved energy efficiency, achieving a reduction in aggregation energy by 8.70%, 10.81%, and 7.98%, as well as a reduction in aggregation time by 13.71%, 18.60%, and 9.84%, respectively. The results showed that the OPT-FIS provides a scalable, energy-efficient, and adaptive approach to data aggregation in underwater wireless sensor networks.

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INTRODUCTION

Wireless sensor networks (WSNs) play a vital role in today's technology by allowing continuous monitoring of environmental factors, infrastructure conditions, and other key variables. Their importance lies in applications that require quick access to data for informed decisions. These systems are made up of multiple compact nodes, each fitted with sensors to collect information (Kathiroli & Kanmani, 2024) . In the late 20th century, interest in wireless sensor networks grew significantly. At first, these networks were only used on land. However, with advancements in oceanic modem technology, they were eventually adapted for underwater applications (Kaveripakam & Chinthaginjala, 2023).

Underwater Wireless Sensor Networks (UWSNs) enable devices to operate underwater, collecting, processing, and transmitting data for monitoring and exploration at various depths. These devices use sensors to gather information from the aquatic environment and relay it to a surface station, where the data is processed based on specific application needs. UWSNs have been developed for multiple purposes, including

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studying oceanic geological processes, detecting underwater mines, forecasting climate changes, assessing human impact on marine ecosystems, locating oil reserves, preventing accidents, tracking marine life, and securing water borders against unauthorized intrusions (Zhang *et al.*, 2023).

The Sugeno approach provides a structured way to derive fuzzy rules from a given set of input-output data. Instead of using a fuzzy set as the outcome, as in Mamdani rules, Sugeno replaces the "then" part with a function of the input variables. A Takagi-Sugeno rule typically appears as: If x is in set A and y is in set B, then z is f(x,y), where x, y, and z are linguistic variables, A and B are fuzzy sets defined on their respective domains, and f(x,y) is a mathematical function (Cavallaro, 2015; Karimi *et al.*, 2022). The Sugeno-type FIS produces a precise (crisp) output by taking a weighted average of the rule results, whereas the Mamdani-type FIS obtains a crisp value by defuzzifying a fuzzy result. The initial two steps in the inference process (fuzzifying the inputs and applying the fuzzy operator) remain the same for both approaches. However, a key difference lies in the nature of the Sugeno output where its membership functions are either linear or constant (Karimi *et al.*, 2022).

The study of (Habib *et al.* (2018)) addressed the challenge of routing efficiency and energy imbalance in wireless sensor networks with mobile sinks by proposing a starfish routing backbone inspired by biological radial structures. The approach also reduced energy imbalance and operational overhead while improving scalability with increasing network size. However, their fixed canal structures and reliance on static thresholds limit adaptability under dynamic energy states. Ismail *et al.* (2020) proposed an opportunistic routing protocol that enhances reliability and energy efficiency by incorporating three metrics: Advancement Factor (ADVf), Reliability Index (RELi), and Shortest Path Index (SPi).

It used exponential priority functions and holding time calculations to reduce duplicate packets, balance energy use, and avoid void holes. However, its performance degraded in sparse networks due to fewer forwarding options. Song (2020) proposed a cost-efficient design for 3D UWSN by jointly optimizing the density of data sinks and the redundancy in fountain code (FC) based transmissions, while supporting communication QoS requirements. The work introduced a queuing-based analytical model (M/G/1) and formulated an optimization problem to minimize total cost (installation and transmission) subject to reliability and delay constraints. However, the method requires precise modeling of queueing behavior and assumes slotted-Aloha MAC, which may not scale well in dynamic environments due to its high collision probability and inefficiency when node density or traffic load increases.

Zhang *et al.* (2021) proposed a reinforcement learning-based opportunistic routing protocol (RLOR) for UWSNs. The RLOR integrates Q-learning with dynamic timing and a recovery mechanism to select optimal relay nodes based on depth, energy, neighbor count, and transmission probability. Simulation results with 50 to 600 nodes showed higher packet delivery rate, better data integrity, lower energy, and reduced average hops. However, RLOR depends on predefined parameters (γ, β) which may not self-adjust in changing environments. Krishnaswamy and Manvi (2022) introduced a palm tree-inspired data aggregation and routing scheme for underwater wireless sensor networks, using static and mobile software agents to organize nodes into hierarchical structures.

Master and local centres were selected based on residual energy, distance, and angle thresholds, enabling multi-level aggregation via mobile agents. The aggregation time increased linearly with node density and communication range. However, the scheme used fixed thresholds and lacked adaptive decision-making for node selection, which can result in uneven energy usage, poor scalability, and decreased network lifetime when the environment or node behavior changes dynamically.

Subramani *et al.* (2022) introduced a two-stage protocol combining Cultural Emperor Penguin Optimizer-based Clustering (CEPOC) and Grasshopper Optimization Algorithm-based Routing (GOA) for energy-efficient UWSNs. The

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CEPOC dynamically formed clusters and selected cluster heads using a fitness function based on node degree, location, and neighbor distances. However, the method relies on computationally intensive metaheuristics and fixed input parameters.

Ayyadurai *et al.* (2023) presented a cluster-based routing algorithm that integrates fuzzy C-Means (FCM) for node grouping and Cuckoo Search Optimization (CSO) for optimal cluster head selection. Nodes were organized into clusters based on proximity, and the most suitable transmission nodes were selected by CSO to minimize delay and energy use. Their approach also showed good packet delivery rate and improved network lifetime. However, its reliance on static cluster definitions and algorithmic complexity limits real-time adaptability. In the work of Sun *et al.* (2023) they presented a multi-objective routing protocol (MOR) designed for both delay-sensitive (DS) and delay-insensitive (DIS) UWSNs. It introduced separate relay selection algorithms tailored to delay using energy consumption, queue length, and hop distance as decision factors. The DS routing minimized delay through congestion- and delay-aware link cost functions, while DIS routing focused on link reliability and energy balancing through expected transmission counts. However, MOR relies on predefined weight tuning and assumes accurate queue-length and energy estimation.

In the work of Luo *et al.* (2024), they proposed a cluster routing algorithm based on a multi-objective differential chaotic shuffled frog leaping algorithm (MDCSFLA) to optimize energy usage, network lifetime, and Quality of Service (QoS). The method integrated differential local search and chaotic perturbation to avoid local optima and improve convergence. It considered factors like residual energy, energy balance, transmission delay, packet loss, and distance to the sink. However, the method relies on complex parameter tuning and high computation overhead. The reviewed literature reveals that although various routing and clustering techniques have been proposed to improve energy efficiency, data aggregation, and network lifetime in UWSNs, many still rely on complex metaheuristics, predefined thresholds, or static decision rules that limit adaptability in dynamic environments.

Several methods, including those based on reinforcement learning, swarm intelligence, or multi-objective optimization, achieved promising results but often required high computational cost, extensive parameter tuning, or centralized control. This gap motivated us to creates an opportunity for the OPT-FIS approach, which integrates a fuzzy inference system to enable adaptive, real-time selection of master and local centres using node features of residual energy, distance, and leaflet angle. Among the available fuzzy logic models, the Sugeno-type fuzzy inference system is selected for this study due to its computational simplicity, real-time efficiency, and ability to produce crisp numerical outputs that are well-suited for algorithmic ranking of node suitability in UWSNs.

This paper comprises five sections. Section 2 provides a detailed overview of underwater acoustic communication. Section 3 outlines the development of a dynamic palm tree architecture for energy-efficient data aggregation using a sugeno fuzzy inference system. Section 4 presents the outcomes and engages in a discourse about the simulation results. Finally, Section 5 wraps up the study by summarizing the contributions of this research.

Underwater Acoustic Communication

Path loss plays a crucial role in underwater acoustic communication, mainly influenced by how far the signal travels and its frequency (Ayyadurai *et al.*, 2023). Absorption loss occurs when acoustic energy turns into heat, which means channel bandwidth should match the intended transmission distance. As operating frequency and the distance between transmitter and receiver grows, so does absorption loss. Power limits also affect how much bandwidth can be used (Jouhari *et al.*, 2019). Underwater acoustic communication bandwidth spans from frequencies below 1 kHz to over 100 kHz. Meanwhile, typical operating frequencies fall between 10 Hz and 1 MHz (Khan *et al.*, 2018a). Different underwater tasks require specific bandwidths and ranges, depending on what needs

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to be accomplished. Data rates for acoustic transmission vary from about 31 kb/s to 125 kb/s, influenced by factors such as channel coding and the quantity of sending and receiving units (Hamilton *et al.*, 2020; Haque *et al.*, 2020).

Routing in Underwater Wireless Sensor Networks

Routing involves determining a suitable route to move information from a starting point to its destination. A UWSN typically includes sensor nodes situated beneath the water's surface, along with a base station generally positioned outside this aquatic setting (Subramani *et al.*, 2022). Because the underwater domain is vast, it becomes crucial to choose ideal placements for each node and find efficient pathways to transfer collected data to the base station. This need underlines the importance of routing in UWSNs (Haque *et al.*, 2020). Data aggregation is a key technique used to combine and collect valuable information in order to conserve energy. In sensor networks with many densely placed nodes, the same data may be recorded multiple times, creating unnecessary redundancy. By applying data aggregation methods, this redundancy can be removed (Shovon & Shin, 2022). Its primary objective is to gather and integrate information in an energy-efficient manner, ultimately increasing the network's operational lifespan (Bhajantri, 2018; Haruna *et al*, 2025).

Fuzzy inference system

A fuzzy inference system (FIS) applies an expert's knowledge to shape the design of a controller. It uses fuzzy control rules (often expressed in IF–THEN format) to define how inputs relate to outputs (Yadav, 2021) . Fuzzy reasoning involves two key elements. First, there are the labels and membership functions linked to the system's inputs and outputs; selecting these with care is one of the most crucial parts of the design. Second, there is the rule base, which transforms fuzzy input values into fuzzy outputs (Cavallaro, 2015).

A FIS typically includes three main parts. The first is the fuzzification stage, which takes a precise input and converts it into a linguistic form using membership functions stored in its knowledge base. The second element, the inference engine, determines how well the input matches the fuzzy sets for the output by following established fuzzy rules. Lastly, the defuzzification process turns the fuzzy conclusion back into a specific, non-fuzzy value (Camastra *et al.*, 2015; Murnawan *et al.*, 2021; Momoh *et al*., 2025).

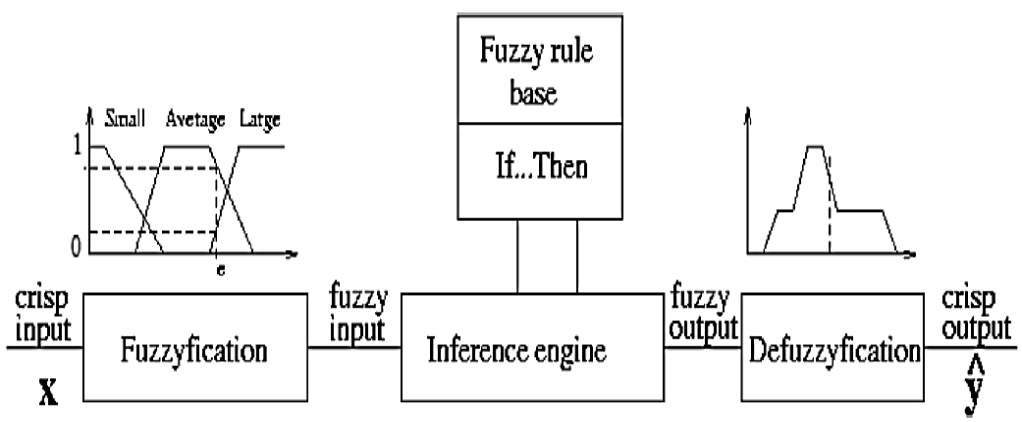

Figure 2.1: An Illustration of the Fuzzy Inference Framework (Alakhras *et al.*, 2020)

As shown in Figure 2.1, a fuzzy inference system typically follows three steps: (i) fuzzification, where fuzzy sets for the linguistic variables are created, (ii) combining all relevant fuzzy rules, and (iii) defuzzification, which transforms the fuzzy result into a non-fuzzy value

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suitable for further use (Alakhras *et al.*, 2020). At the core of the FIS, the inference engine simulates human decision-making through approximate reasoning, guiding the system toward an effective control strategy (Camastra *et al.*, 2015). During this inference process, fuzzy inputs activate the relevant fuzzy rules, resulting in a corresponding fuzzy output. Figure 2.2 provides a general overview of the structure of such a fuzzy expert system (Cavallaro, 2015).

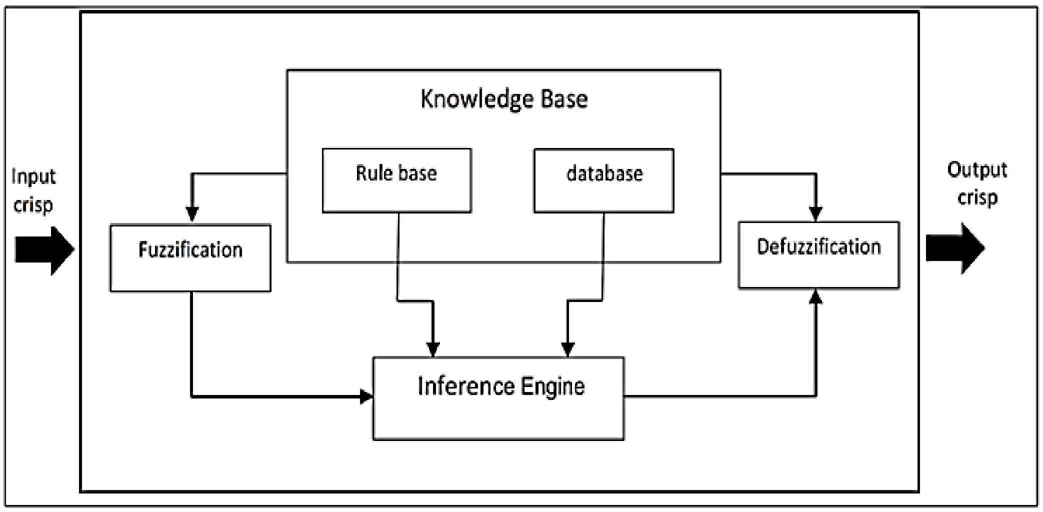

Figure 2.2: The Design of a Fuzzy Expert System (Cavallaro, 2015)

In a fuzzy inference model, often called approximate reasoning, the thought process relies on a series of if-then rules reflecting expert understanding (Bhaskarwar & Pete, 2021). Each conditional statement consists of an if-part (the premise) and a then-part (the conclusion). Within a fuzzy control system, knowledge is represented as a collection of rules, such as "if X is A then Y is B," or more generally, "if X_I is A_1 and ... and X_n is A_n then Y is B", where A, A_n, B are fuzzy sets. The knowledge base as seen in Figure 2.2, which includes general information about the problem domain, links premises to conclusions (Cavallaro, 2015).

To demonstrate how the stages of a fuzzy inference system work, we start by converting the precise input values X_i into fuzzy sets $\tilde{X}_i$, according to their respective input spaces. Second, the input fuzzy sets $\tilde{x}_1, \tilde{x}_2, \ldots, \tilde{x}_n)$ are compared with the corresponding if-part fuzzy sets in each rule's antecedent. This comparison is represented as (Alakhras *et al.*, 2020):

$$a_i^j = S\left(A_i^j, \hat{X}_i\right) \qquad (0.1)$$

Here, S is a function used to evaluate how well the input fuzzy sets align with the antecedents defined in each fuzzy rule. Common choices for the S function include the max operator and other t-conorms (Alakhras *et al.*, 2020).

Third, the individual matching degrees a_i^j obtained from all n input fuzzy sets for a given rule are combined using a T operator (Alakhras *et al.*, 2020):

$$\mu_j = T\left(a_1^j, \ldots, a_n^j\right) \qquad (0.2)$$

Typical T operators include the minimum function, the product, or more general t-norm connectives.

Fourth, the computed value μ_j activates the corresponding rule's output fuzzy set Y_j (Alakhras *et al.*, 2020). In many fuzzy system models, Y_j is represented by its centroid, leading to:

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$$f_j = f\left(\mu_j, Y_j\right) \tag{0.3}$$

Fifth, the results from all activated rules, $f_j, j = 1,2,\ldots,m$, are combined into one final output fuzzy set (Alakhras *et al.*, 2020) as:

$$y = g\left(f_1, f_2, \ldots, f_m\right) \tag{0.4}$$

In practice, a Mamdani-type fuzzy inference system commonly applies the centre-of-gravity method for defuzzification, while a Takagi-Sugeno approach often uses a weighted average based on membership values (Alakhras *et al.*, 2020; Karimi *et al.*, 2022).

Palm tree network architecture

The palm-tree-inspired architecture is designed to manage both data aggregation and routing in underwater sensor networks. In this approach, the sink node triggers the process by sending a request to collect data, which is then aggregated as it flows upward through the network hierarchy, enhancing scalability (Krishnaswamy & Manvi, 2022). At the top, the crown symbolizes the palm canopy. Within this canopy, spines branch out, each bearing leaflets connected at a junction by petioles. Each leaflet attaches to the leaf via a rachis and collectively covers every node in the Underwater Wireless Acoustic Sensor Network (UWASN). Where petioles meet the spines, a master centre node is assigned per spine. A local centre node represents the rachis link to the spine (Krishnaswamy & Manvi, 2022).

Palm tree structure

Below are key terms related to the palm tree architecture (Krishnaswamy & Manvi, 2022):

1. Palm tree structure: This represents the network's overall form, including leaflets/fronds and a sink node, with numerous intermediate nodes in between.
2. Master centre node: This is an intermediate node located where petioles meet. It gathers aggregated data from leaflets connected through local-level aggregation.
3. Local centre node: Another intermediate node placed along the rachis of a leaflet. Local aggregation is performed here to eliminate redundant information collected from nearby underwater sensor nodes.
4. Number of neighboring UW-sensor nodes: The total count of active underwater sensor nodes within a certain communication range.
5. Residual Energy: This defines the energy remaining in the node's battery. The choices reflect typical WSN energy profiles and support intelligent decision-making for energy conservation.
6. Distance to Master Node: This is the distance between a sensor node and its associated master node, bounded within the communication range R. The range is expressed as $d_m \in [0, R]$, where R is the communication range.
7. Petiole angle: The angle describing where the master centre node is located, measured from a reference direction extending from the sink to nearby underwater sensor nodes.
8. Leaflet angle: The angle formed between the leaflets along the rachis and the local centre on the spine, referenced against the main (midrib) axis.
9. Energy-to-distance ratio: is a critical feature for assessing the suitability of a node for data aggregation and relay operations. It combines two essential factors which are residual energy (E_r) and distance to the master node (d_m). The ratio is calculated as:

$$R_{e-d} = \frac{E_r}{d_m + \grave{o}} \tag{2.5}$$

In equation **Error! Reference source not found.**, ϵ is a small positive constant to avoid division by zero.

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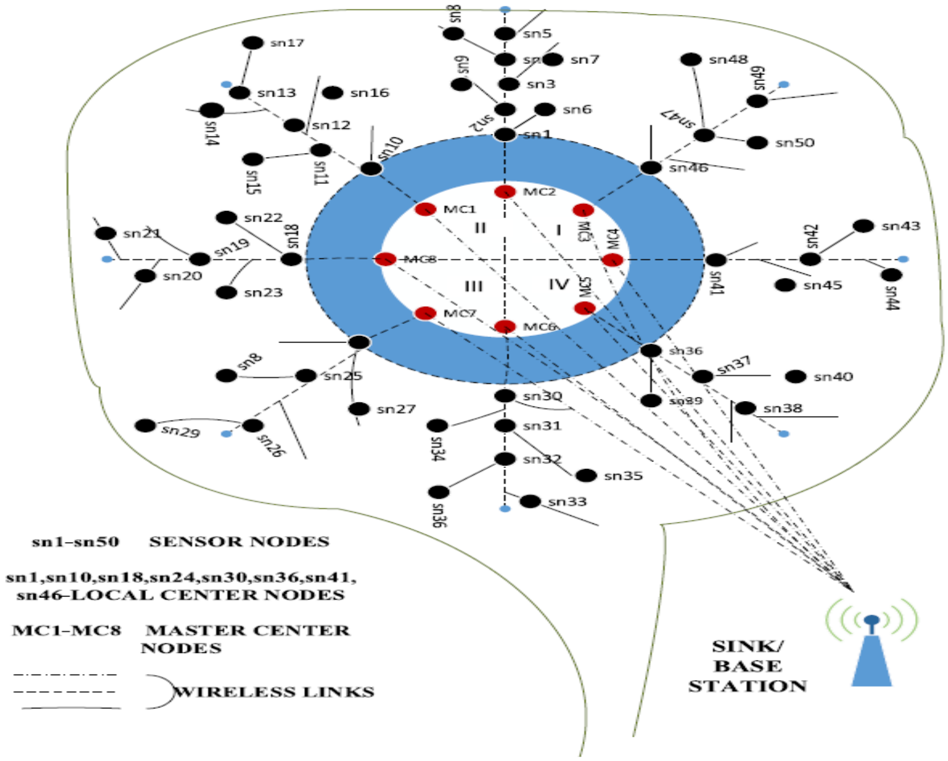

Figure 2.3: Environment of a Palm Tree-Structured Network (Krishnaswamy & Manvi, 2022)

The data aggregation framework, shown in Figure 2.3, illustrates the positions of the sink, local centres, and master centres arranged along the leaflets and at the junctions of the petioles in a palm tree structure. Each local centre collects and consolidates data from its neighboring underwater sensor nodes. A local aggregation agent (LAA), started by the final local centre, then gathers this aggregated information and forwards it to the appropriate master centre. In a similar way, the master aggregation agent (MAA), activated by the last master centre, combines the data from all master centres and delivers it to the sink (Krishnaswamy & Manvi, 2022). Table 2.1 lists the notations used to describe the system.

Table 2. 1: Notations (Krishnaswamy & Manvi, 2022)

Descriptions	**Symbols**
Communication range of UW-sensor node	R
Neighbour node count	N_c
Weight factor of Master(m)/Local (l) centre selection	W_f/W_l
Arbitrary radius of junction of petioles	r
Number of petioles	N_p

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Descriptions	Symbols
Initial energy of every node	E_i
Residual/Utilized energy of every node	E_{R_t}/E_u
Euclidean distance between nodes l and m	$E_{d_{l,m}}$
Threshold distance of master/local centre	D_{pth}/D_{lth}
Angle between master centre/petiole and node i	θ_{p_i}
Total number of leaflets connected to the spine	La_{total}
Degree of neighbor nodes	D_{nth}
Distance between petioles	P_d
Petiole angle	θ_p
Angle between petioles	θ_{petiole}
Probability of occurrence of redundant data	$P_{R_{da}}$
Redundant data set	R_{da}
Angle between local centre/leaflet and node i	θ_{l_i}
Probability of aggregated data	P_{Ag}
Data aggregation time at master/local centres	Ma_{agtime}/La_{agtime}
Time required to aggregate from leaflet	T_{leaf}
Total time for aggregation	To_{agtime}

Selection procedure for petiole/master centres

Petioles emerge from their junction located at the upper part of the palm's trunk. The distance between petioles, denoted as P_d (Krishnaswamy & Manvi, 2022), can be calculated by:

$$P_d = 2 \times R \times D_{nth} \tag{0.5}$$

The number of petioles in the crown's junction area, N_p (Krishnaswamy & Manvi, 2022), is determined by:

$$N_p = \frac{2\pi r}{P_d} \tag{2.7}$$

The junction's radius r in equation (2.8) (Krishnaswamy & Manvi, 2022) is found using:

$$r = R \times D_{nth} \tag{2.8}$$

The value of D_{nth} in equation (2.8) (Krishnaswamy & Manvi, 2022) is chosen based on the desired number of direct and indirect neighbors for data aggregation. The petiole angle, $\theta_{\text{petiole}}\ p$, is given as:

$$\theta_{\text{petiole}} = \frac{360^{\circ}}{N_p} \tag{2.9}$$

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In equation (2.9) (Krishnaswamy & Manvi, 2022), the angle sets the spacing between petioles. The angle of a specific petiole p, denoted θ_p, for p $= 1,2,\dots,N_p$, is computed as:

$$\theta_p = \theta_{\text{petiole}} \times p \tag{2.10}$$

The petiole angle between neighboring underwater sensor nodes at the junction (considering node l and node m) is computed as:

$$\theta_{p_{(i)}} = \tan^{-1}\frac{(y_l - y_m)}{(x_l - x_m)} \tag{2.11}$$

where (x_l, y_l) and (x_m, y_m) represent the coordinates of node l and node m in equation (2.11), respectively (Krishnaswamy & Manvi, 2022).

Master centre selection depends on which quadrant of the circle the petiole lies in. The junction of the petioles is considered as a circle, so the following four cases arise (Krishnaswamy & Manvi, 2022):

1. Case I: If $x_l > x_m$ and $y_l > y_m$, master centre selection occurs in the first quadrant.
2. Case II: If $x_l < x_m$ and $y_l > y_m$, master centre selection occurs in the second quadrant.
3. Case III: If $x_l < x_m$ and $y_l < y_m$, master centre selection occurs in the third quadrant.
4. Case IV: If $x_l > x_m$ and $y_l < y_m$, master centre selection occurs in the fourth quadrant.

The remaining (residual) energy, E_{R_t} (Krishnaswamy & Manvi, 2022), available at each underwater sensor node can be found using:

$$E_{R_t} = |E_i - E_u| \tag{2.12}$$

where E_i is the node's initial energy and E_u is the amount of energy it has already utilized in equation (2.12) (Krishnaswamy & Manvi, 2022). The Euclidean distance between any underwater sensor node l and a neighboring node m is determined by:

$$E_{d_{l,m}} = \sqrt{|x_l - x_m|^2 + |y_l - y_m|^2} \tag{2.13}$$

In equation (2.13) (Krishnaswamy & Manvi, 2022), the weight factor W_f for a given underwater sensor node depends on the number of nearby nodes N_c and the node's residual energy at time tE_{R_t}. The sink node's UWSMA starts the master selection procedure by sending a query to its neighboring nodes. In response, each neighbor's UWNMA calculates its own W_f and returns both its position and W_f to the sink node's agent. The weight factor is computed as:

$$W_f = K\left(E_{R_t} \times N_c\right) \tag{2.14}$$

where K is a constant value between 0 and 1 in equation (2.14).

During master centre selection at the petiole junction, underwater sensor nodes positioned at angle θ_p are considered. Each node's threshold distance is represented as D_{pth}. If $E_{d(l,m)} > D_{pth}$, the underwater sensor node is eligible to compete for the master centre role. Among the competing neighbors, the node with the highest W_f is chosen by the UWSMA as the master centre (Petiole Aggregator - PA) (Krishnaswamy & Manvi, 2022).

If no suitable contender meets the threshold $(E_{d_l l,m)} > D_{pth})$, then D_{pth} is adjusted (either increased or decreased) to find other candidates for PA selection. Once the first PA is selected at a given petiole angle, the UWSMA of that master centre triggers PASA. The PASA continues identifying subsequent PAs until it reaches the final master centre in the network. Throughout this process, PASA carries the IDs of each master centre to form a path linking all of them together (Krishnaswamy & Manvi, 2022).

Designing an optimized palm tree fuzzy inference system (OPT-FIS)

This subsection details the development of the OPT-FIS, which leverages fuzzy logic for efficient selection of local and master centres,

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optimizing energy use and data aggregation in UWSNs.

Fuzzy logic system initialization

To select suitable local centre nodes dynamically, a FIS is designed and implemented. The system takes four inputs: leaflet angle (θ_{lm}), residual energy (E_r), distance to master node (d_m), and energy-to-distance ratio (R_{e-d}). Each input was assigned three gaussian membership functions (MFs): Low, Medium, and High. These are presented in Table 3.2.

Table 3. 1: Membership Function Parameters for OPT-FIS Input Variables

Input Variable	**Fuzzy Set**	**Type**	**Support Range**	**Centre / Peak**	**Description**
Leaflet Angle (θ ∈ [0, 360])	Low	Gaussian	Full support	60°	Nodes aligned at narrow angles
	Medium	Gaussian	Full support	100°	Moderately aligned nodes
	High	Gaussian	Full support	270°	Nodes at wide angles
Residual Energy (E ∈ [0, 10])	Low	Gaussian	Full support	2	Nodes with low battery levels
	Medium	Gaussian	Full support	6	Nodes with medium energy
	High	Gaussian	Full support	9	Nodes with sufficient energy
Distance to Master Node (d_m ∈ [0, R])	Near	Gaussian	Full support (scaled by R)	¼ R	Nodes close to master
	Medium	Gaussian	Full support (scaled by R)	½ R	Nodes at moderate distance
	Far	Gaussian	Full support (scaled by R)	¾R	Nodes far from master
Energy-to-Distance Ratio (Re-d)	Low	Trapezoidal	[0, 0.5]	Peak at 0 to 0.3	Unfavorable (low energy or far distance)
	Medium	Triangular	[0.3, 0.7]	Peak at 0.5	Moderately suitable nodes
	High	Trapezoidal	[0.5, 1]	Peak at 1	Favorable (high energy and short distance)

1. Leaflet Angle (θ_{lm}) : The centres (60, 100, and 270 degrees) for low, medium, and high, respectively. The MFs are chosen based on network geometry and data distribution. The 60 degree represents nodes aligned in narrow angles, found in clustered topologies, where nodes share minimal overlapping communication areas. The 100 degree represents nodes with moderate angles, typically aligned in general network coverage scenarios, balancing redundancy and efficiency. The 270 degree represents nodes at wide angles in high-redundancy regions.
2. Residual Energy (E_r) : The parameters (2, 6, 9) and spreads (4^2, 2.8^2, 10^2) are chosen to reflect low, medium, and high

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energy distribution of the network, ensuring efficient resource allocation and prolonged network operation.

3. Distance to Master Node (d_m) : The centres of the membership functions are scaled relative to the communication range (R) of the sensor node to reflect spatial distribution.

Energy-to-Distance Ratio (R_{e-d}) : Re-d is computed using equation (2.5), where ε = 0.001. ε is used to prevent division by zero. It is chosen to be small enough not to affect valid distance measurements, while ensuring numerical stability when nodes are extremely close to the master node.

Nodes with unfavorable energy-to-distance ratios.

$$MF_{\text{Low}}\left(R_{e-d}\right)=\begin{cases}1 & \text{if } R_{e-d}\leq 0.3\\ \dfrac{0.5-R_{e-d}}{0.5-0.3} & \text{if } 0.3<R_{e-d}\leq 0.5\\ 0 & \text{if } R_{e-d}>0.5\end{cases} \quad (3.1)$$

Nodes with moderately favorable ratios

$$MF_{\text{Medium}}\left(R_{e-d}\right)=\begin{cases}\dfrac{R_{e-d}-0.3}{0.5-0.3} & \text{if } 0.3<R_{e-d}\leq 0.5\\ \dfrac{0.7-R_{e-d}}{0.7-0.5} & \text{if } 0.5<R_{e-d}\leq 0.7\\ 0 & \text{otherwise}\end{cases} \quad (0.6)$$

Nodes with favorable ratios

$$MF_{High}\left(R_{e-d}\right)=\begin{cases}0 & \text{if } R_{e-d}\leq 0.5\\ \dfrac{R_{e-d}-0.5}{1-0.5} & \text{if } 0.5<R_{e-d}\leq 1\\ 1 & \text{if } R_{e-d}>1\end{cases} \quad (3.3)$$

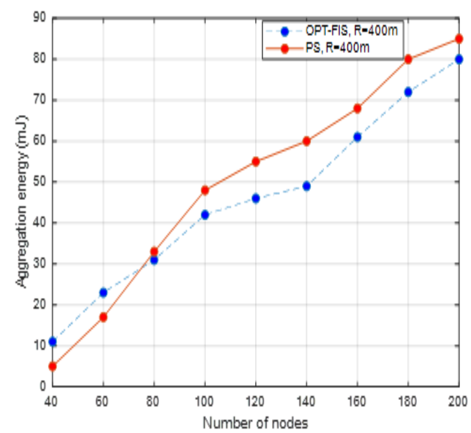
The ratio balances energy consumption and communication efficiency. Higher R_{e-d} implies nodes are both energy-efficient and close to the master node, making them suitable for aggregation. Lower R_{e-d} reflects poor energy or large distances, discouraging their selection.

RESULT AND DISCUSSION

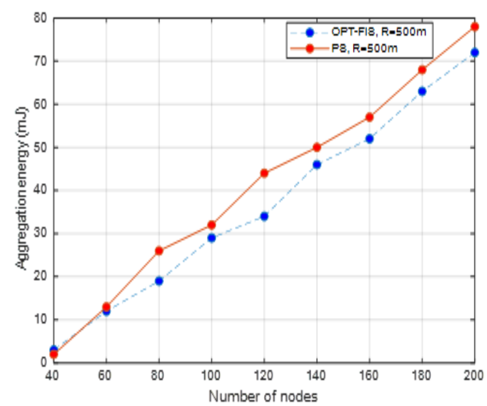
This section presents the results of the OPT-FIS performance evaluation. The analysis focuses on aggregation energy, aggregation time, aggregation ratio, and network lifetime as it performance metrics. These metrics provide insights into the effectiveness of the OPT-FIS in enhancing data aggregation and energy efficiency in UWSNs.

Aggregation energy

The performance of the OPT-FIS is evaluated based on energy consumption during data aggregation. The results are analyzed and compared in Figures 4.1 across three different communication ranges of 400 m, 500 m, and 600 m.



(a)



(b)

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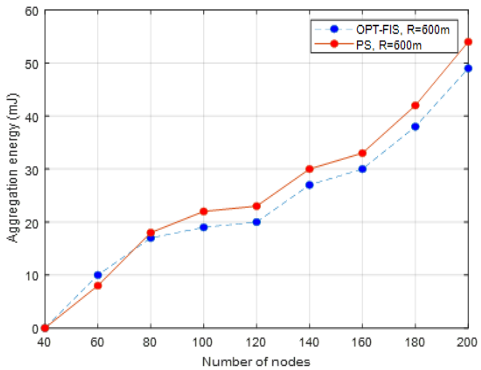


(c)
Figure 4.1: Aggregation Energy Against the Number of Nodes Across (a) 400 (b) 500 and (c) 600 Meters Communication Range

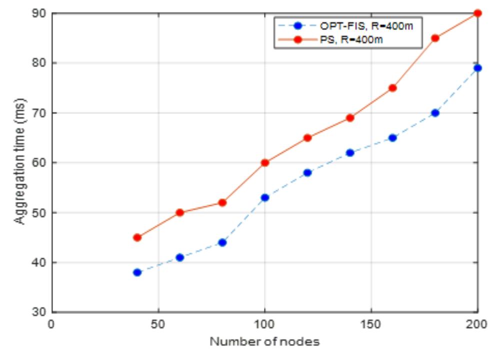
Figure 4.1a shows the variation in aggregation energy with respect to the number of nodes for a 400m communication range. The OPT-FIS demonstrates lower aggregation energy consumption compared to the baseline method (PS). This is due to the efficient selection of master and local centres, minimizing redundant data aggregation. The energy savings becomes more obvious as the number of nodes increases beyond 100. The reduced energy consumption reflects the effectiveness of the OPT-FIS structure in optimizing data aggregation.

In Figure 4.1b, for a 500m communication range, the results indicate a similar trend. The aggregation energy for the OPT-FIS remains lower than the PS, even as the number of nodes increases. As the communication range increases, the OPT-FIS effectively manages node connectivity and reduces energy use.

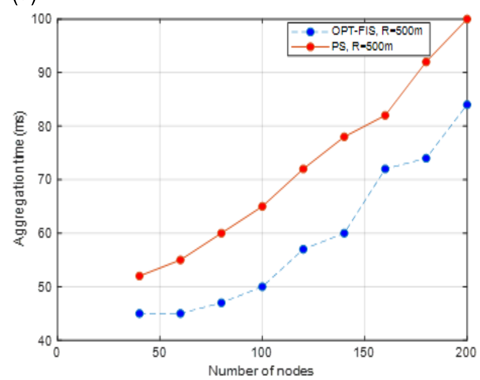
Figure 4.1c illustrates the results for a 600m communication range. The extended communication range introduces more connected nodes, resulting in higher aggregation energy. Compared to the results of the PS method, the OPT-FIS consistently demonstrates better performance across all communication ranges. While the PS exhibits a linear increase in energy consumption with the number of nodes, the OPT-FIS method maintains a controlled rise. This improvement can be attributed to the local centre selection strategy, which optimize the aggregation process by reducing unnecessary data transmissions and processing.

Aggregation time

The same communication ranges of 400, 500, and 600 meters were used to assess the aggregation time results, as shown in Figure 4.2.



(a)



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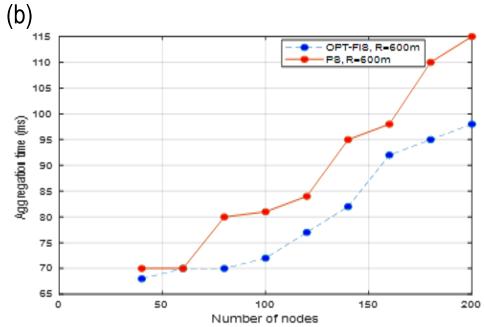

(c)
Figure 4.2: Aggregation Time Against the Number of Nodes Across (a) 400 (b) 500 and (c) 600 Meters Communication Range

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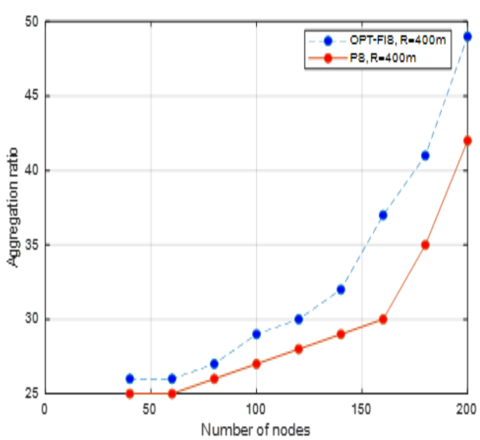
As seen in Figure 4.2a, the OPT-FIS consistently shows lower aggregation time compared to the PS for a 400m communication range. The time difference becomes more significant as the number of nodes increases. Figure 4.2b reveals a similar trend for the 500m communication range. The OPT-FIS maintains lower aggregation times across all node densities, with a notable gap emerging as the network grows deeper. For the 600m communication range, as illustrated in Figure 4.2c, the OPT-FIS continues to outperform the PS in terms of aggregation time, with the difference becoming more pronounced beyond 100 nodes. This consistent improvement reflects the system's stabilization over time, where the benefits of distributed aggregation and efficient routing compensate for the minor delays seen during initial setup.

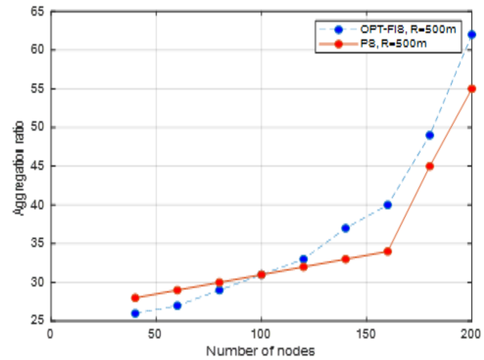
While the PS shows slightly better performance in energy and time for smaller networks (40 to 80 nodes), the OPT-FIS demonstrates advantages in larger and more complex n setworks, validating its scalability and overall efficiency. Lower aggregation time often corresponds to reduced energy consumption, as faster aggregation minimizes the duration of data transmission and processing.

Aggregation ratio

The results for aggregation ratio are analyzed in Figures 4.3 across communication ranges of 400m, 500m, and 600m.



(a)



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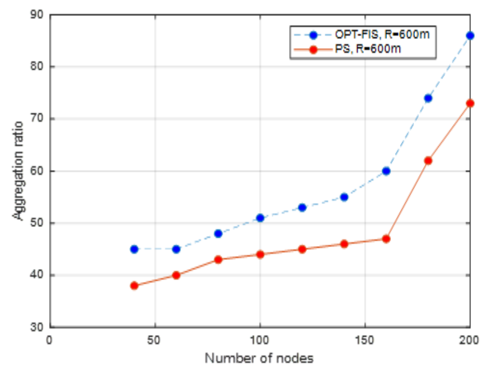

(c)

Figure 4.3: Aggregation Time Against the Number of Nodes Across (a) 400 (b) 500 and (c) 600 Meters Communication Range

In Figure 4.3a, the OPT-FIS achieves a higher aggregation ratio than the PS for the 400m range. As the number of nodes increases, the gap in performance broadens, with the OPT-FIS reaching a higher aggregation ratio at 200 nodes. Figure 4.3b illustrates the aggregation ratio for the 500m communication range. Similar to the 400m range, the OPT-FIS outperforms the PS as the network becomes deeper. For the 600m range shown in Figure 4.3c, the OPT-FIS continues to demonstrate a better aggregation ratio than the PS. As the number of nodes increases, the advantage of the OPT-FIS becomes more apparent. The superior aggregation ratio of the OPT-FIS across all communication ranges highlights its ability to aggregate data more effectively than the PS. This improvement aligns

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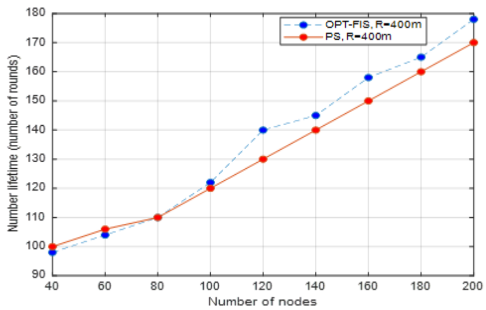
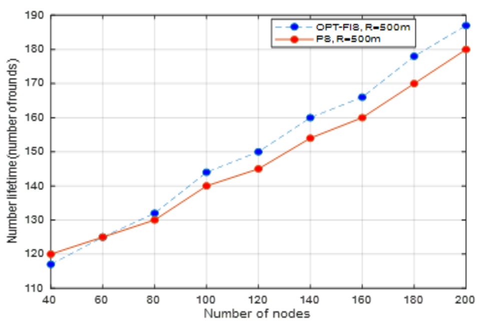
with the reduced aggregation time and energy seen in previous results, as efficient aggregation processes reduce redundancy and increase the proportion of useful aggregated data.

Network lifetime

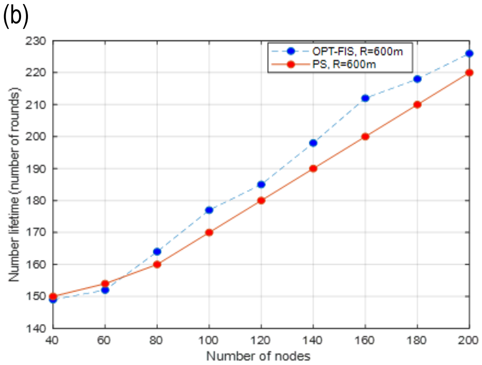
The network lifetime findings were assessed using the same communication ranges of 400, 500 and 600 meters, as illustrated in Figure 4.4.



(a)



(b)



(c)

Figure 4. 4: Network Lifetime Against the Number of Nodes Across (a) 400 (b) 500 and (c) 600 Meters Communication Range

In Figure 4.4a, the network lifetime for both the OPT-FIS and PS increases with the number of nodes. However, the OPT-FIS consistently achieves a longer network lifetime compared to the PS, particularly as the number of nodes expands. As shown in Figure 4.4b for the 500m communication range, the OPT-FIS maintains its advantage over the PS in terms of network lifetime. The gap becomes more significant as the network grows denser. In Figure 4.4c, the OPT-FIS demonstrates the highest improvement in network lifetime for the 600m communication range. Although the PS method also improves as the number of nodes increases, it shows a lower overall network lifetime due to less effective energy management. On the other hand, the OPT-FIS achieves better energy efficiency through its adaptive node selection using a fuzzy inference system, which considers residual energy, distance, and node positioning. By dynamically selecting local centres based on current network conditions, it reduces unnecessary transmissions and balances the energy load across nodes.

CONCLUSION

The results obtained confirm that the optimized palm tree fuzzy inference system (OPT-FIS) improves energy efficiency and data aggregation in UWSNs compared to the PS method. In aggregation, OPT-FIS demonstrated improvements of 8.70%, 10.81%, and 7.98% for the ranges 400m, 500m, and 600m, respectively. These improvements are due to the hierarchical structure and dynamic selection of master and local centres, which reduce redundant data processing and enhance aggregation efficiency. To sum it up, these results validate that OPT-FIS provides a more scalable and energy-efficient approach to data aggregation in UWSNs.

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