



Contents lists available at FOMJ

Fuzzy Optimization and Modelling Journal

Journal homepage: <https://sanad.iau.ir/journal/fomj/>**Paper Type: Research Paper**

A Hybrid Fuzzy-Genetic Algorithm for Energy-Efficient Routing in Wireless Sensor Networks

Ahmad Jalili ^{a,*}^a *Department of Computer Engineering, Gonbad Kavous University, Gonbad Kavous, Iran*

ARTICLE INFO

Article history:

Received 20 September 2024

Revised 30 November 2024

Accepted 16 December 2024

Available online 28 December 2024

Keywords:

Wireless Sensor Networks

Clustering

Fuzzy Logic

Genetic Algorithms

Energy Efficiency

ABSTRACT

Wireless Sensor Networks (WSNs) encounter considerable challenges in terms of energy efficiency and network longevity due to their limited energy resources. This paper proposes a novel hybrid clustering-based routing protocol that addresses these challenges by integrating fuzzy logic for dynamic and adaptive cluster head (CH) selection based on residual energy, node degree, and proximity, and genetic algorithms (GA) for optimising cluster formation by balancing energy consumption and minimising communication distances. The protocol's objectives are threefold: to minimise energy consumption, extend network lifespan, and enhance Quality of Service (QoS). The proposed method was simulated in MATLAB and benchmarked against the LEACH and TEEN protocols. The results demonstrated the protocol's superior performance, achieving a 30% reduction in energy consumption, a 25% increase in network longevity, and higher data reliability. The primary factors contributing to this enhanced performance are the integrated use of fuzzy logic for optimised cluster head selection and genetic algorithms for optimal cluster formation. The findings substantiate the protocol's capacity to substantially enhance the energy efficiency and scalability of WSNs, providing a resilient and pragmatic solution for practical applications in real-world settings.

1. Introduction

Wireless Sensor Networks (WSNs) have emerged as a transformative technology with diverse applications, including environmental monitoring, healthcare, agriculture, and military operations [16]. These networks consist of distributed sensor nodes that monitor physical or environmental conditions and relay the collected data to a centralized base station. The inherent advantages of WSNs—such as low-cost deployment, scalability, and adaptability—have propelled their adoption in both research and industrial domains [5].

Despite their benefits, WSNs face significant challenges that hinder their performance and reliability. Chief among these is the limited energy capacity of sensor nodes, which often operate on non-rechargeable batteries. Inefficient energy usage can lead to premature node failure, compromising data collection and network

^{*} Corresponding authorE-mail address: jalili@gonbad.ac.ir

functionality [9]. Additionally, the dynamic and resource-constrained environments in which WSNs are deployed exacerbate the challenge of optimizing their performance.

To address these challenges, clustering-based routing protocols have been widely adopted. These protocols group sensor nodes into clusters, with a designated cluster head responsible for aggregating and transmitting data to the base station. This reduces the number of direct transmissions, thereby conserving energy and prolonging network lifespan. Prominent examples of such protocols include LEACH (Low-Energy Adaptive Clustering Hierarchy) [13] and TEEN (Threshold-sensitive Energy Efficient Network) [6]. While these methods have shown promise, they suffer from limitations such as suboptimal cluster head selection, uneven energy distribution, and reduced scalability in large-scale networks.

Recent advancements in computational intelligence, such as fuzzy logic and genetic algorithms, provide new opportunities to enhance clustering efficiency. Fuzzy logic enables the dynamic selection of cluster heads based on multiple criteria, such as residual energy, proximity, and node degree. Simultaneously, genetic algorithms offer robust optimization capabilities, refining cluster configurations to achieve balanced energy consumption and minimized transmission distances.

Despite significant progress in WSN routing protocols, existing methods often fail to achieve optimal energy efficiency and network longevity, particularly in heterogeneous and large-scale deployments. Many approaches overlook the dynamic nature of network conditions and rely on static or heuristic clustering methods, leading to inefficiencies in energy usage and increased data redundancy. A robust, adaptive, and scalable solution that combines intelligent decision-making with optimization techniques is still lacking in the field [2].

This study aims to address these limitations by developing a hybrid clustering-based routing protocol that integrates fuzzy logic and genetic algorithms. The proposed protocol dynamically selects optimal cluster heads using fuzzy logic, while genetic algorithms optimize cluster formation to balance energy consumption and extend network lifespan. The protocol is evaluated through MATLAB simulations, demonstrating superior performance in energy efficiency, network longevity, and data reliability compared to traditional methods. By bridging the gap between computational intelligence and WSN optimization, this study contributes a novel approach to enhancing the efficiency and robustness of wireless sensor networks, paving the way for improved real-world applications in diverse and resource-constrained environments.

The remainder of this paper is organized as follows: Section 2 reviews related works and outlines existing approaches to clustering-based routing in WSNs. Section 3 details the proposed hybrid clustering-based routing protocol, including its system model, clustering, and routing phases. Section 4 presents the simulation setup and evaluates the performance of the proposed method. Finally, Section 5 concludes the study and discusses future research directions.

2. Related Works

Wireless Sensor Networks (WSNs) have garnered significant research attention due to their versatility and diverse applications. Efficient energy management and data transmission are critical to prolonging the network's lifespan. Clustering-based routing protocols have emerged as a popular solution, addressing the energy constraints of WSNs [11]. This section provides an overview of traditional clustering methods, their limitations, and recent advancements incorporating computational intelligence techniques.

Cluster-based routing algorithms are designed to improve energy efficiency by organizing sensor nodes into clusters, where each cluster has a designated Cluster Head (CH). The CH is responsible for aggregating data from its member nodes and transmitting the aggregated data to the Base Station (BS), either directly or through multi-hop communication. This approach reduces the number of direct transmissions to the BS, thereby conserving energy and prolonging network lifetime. Additionally, clustering enhances network scalability and facilitates efficient resource management in large-scale deployments. However, these algorithms face challenges such as optimal CH selection, balancing energy consumption among nodes, and adapting to dynamic network conditions.

One of the pioneering protocols in clustering-based routing is the Low-Energy Adaptive Clustering Hierarchy (LEACH), which utilizes randomized rotation of cluster heads (CHs) to balance energy consumption across nodes [8]. LEACH is designed for single-hop communication between CHs and the base station, making it efficient in homogeneous networks. However, it suffers in scalability and adaptability to heterogeneous environments.

Building upon LEACH, protocols like TEEN (Threshold-sensitive Energy Efficient Network) and APTEEN (Adaptive Periodic Threshold-sensitive Energy Efficient Network) were introduced to support time-sensitive applications. TEEN focuses on event-driven communication by defining hard and soft thresholds for data transmission, reducing energy usage but limiting its applicability to periodic data monitoring scenarios [15].

Another notable approach is PEGASIS (Power-Efficient GATHERing in Sensor Information Systems), which forms a chain of nodes instead of clusters to reduce the number of transmissions to the base station. While this improves energy efficiency, the linear arrangement introduces delays, making it unsuitable for large-scale or delay-sensitive applications [14]. Although these protocols demonstrated significant improvements in energy efficiency, they are not without limitations. Most traditional methods rely on static clustering mechanisms, which fail to adapt to dynamic network conditions. Additionally, they often overlook optimal CH selection, leading to imbalanced energy consumption and reduced network lifespan [17]. These issues underscore the need for more adaptive and scalable solutions.

The integration of computational intelligence techniques into clustering-based routing has shown great promise in recent studies. Fuzzy logic, for instance, has been widely used to address the challenge of dynamic CH selection. By considering multiple factors such as residual energy, node degree, and proximity, fuzzy logic enables a more nuanced and adaptive selection process. Babakordi and Taghi-Nezhad [4] demonstrated that fuzzy logic-based CH selection significantly improves energy efficiency and network performance compared to deterministic methods.

Fuzzy logic has been employed in several studies for CH selection due to its ability to handle uncertainty and adapt to dynamic conditions. For instance, Babakordi and Taghi-Nezhad [4] proposed a fuzzy logic-based method that considers multiple criteria, such as residual energy and node proximity, for CH selection. While this approach improved energy efficiency, it struggled with scalability in large networks and did not consider real-time adaptability. Similarly, Ghasemzadeh et al. [7] integrated fuzzy logic with a clustering protocol, which demonstrated better energy balancing across nodes but faced challenges in heterogeneous environments.

Genetic algorithms (GAs) have also been employed to optimize cluster formation and minimize intra-cluster distances. GAs use evolutionary principles such as selection, crossover, and mutation to identify optimal network configurations. For instance, Babakordi [3] proposed a GA-based clustering approach that outperformed traditional methods in terms of energy consumption and scalability. Other techniques, such as particle swarm optimization (PSO) and ant colony optimization (ACO), have also been explored for clustering and routing optimization. PSO adapts cluster formation based on the movement of particles in the solution space, while ACO mimics the behavior of ants to discover optimal paths for data transmission [1].

Recent studies have also focused on hybrid approaches that combine fuzzy logic with metaheuristic algorithms. For example, Ghasemzadeh et al. [7] integrated fuzzy logic with a genetic algorithm to optimize both CH selection and cluster formation. Their results showed improved network longevity and balanced energy consumption across nodes. Similarly, Jalili et al. [10] proposed a hybrid model combining fuzzy logic with ACO for enhancing routing efficiency in dynamic WSN environments. While these approaches demonstrate the potential of hybrid methods, most fail to address real-time adaptability to node mobility and energy depletion. Furthermore, many methods are limited to homogeneous networks and do not scale well to heterogeneous or large-scale deployments.

While traditional and computational approaches have contributed significantly to clustering-based routing, several gaps remain. Most existing protocols fail to consider real-time adaptability to node mobility and energy depletion. Furthermore, many methods are limited to homogeneous networks and do not scale well to heterogeneous or large-scale deployments. This study addresses these gaps by proposing a hybrid clustering-

based routing protocol that integrates fuzzy logic and genetic algorithms to enhance energy efficiency, scalability, and adaptability in WSNs.

3. Proposed Methodology

The proposed hybrid clustering-based routing protocol integrates fuzzy logic and genetic algorithms to achieve energy-efficient routing and extend the lifespan of WSNs. The methodology involves two key phases—clustering and routing—and incorporates dynamic and adaptive mechanisms for optimal performance.

3.1. System Model

The proposed protocol operates in two phases:

1. **Clustering Phase:** Sensor nodes are grouped into clusters based on their energy levels, spatial proximity, and network topology. Cluster Heads (CHs) are selected dynamically using fuzzy logic to optimize parameters such as residual energy, node degree, and proximity.

2. **Routing Phase:** CHs aggregate data from cluster members and transmit it to the Base Station (BS). Communication occurs either directly or via multi-hop paths, depending on network size and topology.

The protocol operates iteratively over data transmission cycles, ensuring adaptive responses to changes in node energy levels and network topology.

Algorithm 1. Pseudocode for the Hybrid Protocol

Algorithm Hybrid_Clustering_Routing

Input: Nodes N , Base Station BS, Energy Threshold ET

Output: Optimized clusters, Data transmission to BS

```

1. Initialize all nodes  $N$  with energy levels and positions.
2. while Network is operational do
3. Phase 1: Clustering Phase
4. for each node  $n$  in  $N$  do
5. Calculate Fuzzy Score (FS) based on:
   - Residual Energy (RE)
   - Node Degree (ND)
   - Proximity (PR)
6. Select nodes with highest FS as Cluster Heads (CHs).
7. Assign remaining nodes to the nearest CH based on proximity.
8. end for

9. Phase 2: Routing Phase
10. for each CH do
11. Aggregate data from cluster members.
12. Transmit aggregated data to BS:
   - Direct Transmission if CH-to-BS distance < Threshold
   - Multi-Hop Transmission otherwise
13. end for
14. Rotate CH role within each cluster to balance energy.
15. end while

```

The pseudocode is central to understanding the hybrid protocol's functionality. It sequentially outlines the steps involved in cluster formation and data routing. Each line of the pseudocode corresponds to specific operations performed during the two phases.

- **Clustering Phase:** Steps 3–8 in the pseudocode detail the fuzzy logic-based CH selection and cluster formation process.

- **Routing Phase:** Steps 9–14 cover data aggregation, direct or multi-hop transmission, and energy balancing through CH rotation.

3.2. Clustering Phase: Fuzzy Logic for CH Selection

The clustering phase employs fuzzy logic to dynamically select Cluster Heads (CHs), adapting to changing network conditions and optimizing energy consumption and communication efficiency. This approach allows for a more nuanced and adaptive CH selection compared to traditional methods (Algorithm 2).

3.2.1 Fuzzy Logic Framework and Fuzzification

Fuzzy logic evaluates potential CHs based on three input criteria:

1. Residual Energy: Nodes with higher residual energy are prioritized to ensure prolonged operational lifespan and network stability.
2. Node Degree: Nodes with a higher number of neighboring nodes are preferred as they facilitate better intra-cluster communication and data aggregation.
3. Proximity: Nodes closer to the center of their potential cluster or the Base Station (BS) are prioritized to minimize transmission distances and overall energy expenditure.

To quantify these criteria, each input parameter is mapped to fuzzy sets using membership functions, a process known as fuzzification. We define the following fuzzy sets for each parameter:

Residual Energy: {Low, Medium, High} – As shown in Figure 1, we use triangular membership functions to represent these fuzzy sets. The membership function for "Low" energy assigns a high degree of membership to nodes with very little remaining energy, decreasing to zero as energy increases. Conversely, the "High" energy membership function assigns a high degree to nodes with substantial energy reserves. The "Medium" fuzzy set peaks at the mid-point of the energy range. The choice of triangular membership functions provides a balance between simplicity and expressiveness, and offers computational efficiency.

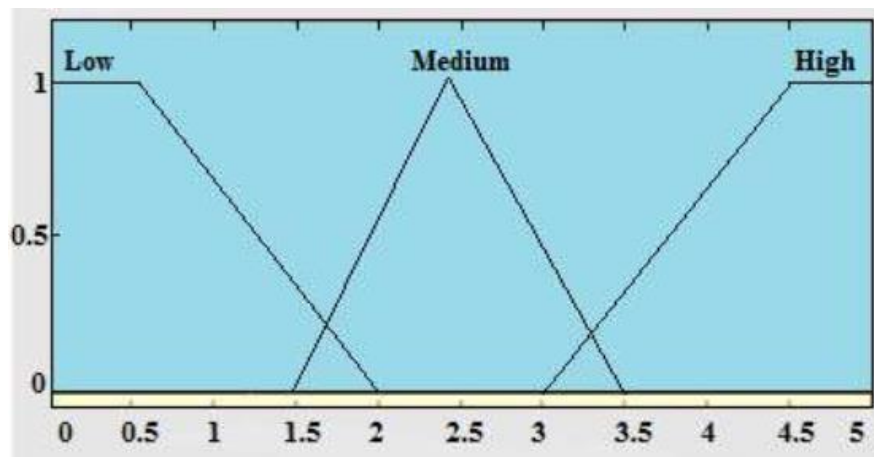


Figure 1. Membership Function for Residual Energy

Node Degree: {Low, Medium, High} – Similar to residual energy, Figure 2 illustrates the triangular membership functions used for node degree. Low or "Sparse" represents nodes with few neighbors, High or "Dense" represents nodes with many neighbors, and "Medium" captures the intermediate range.

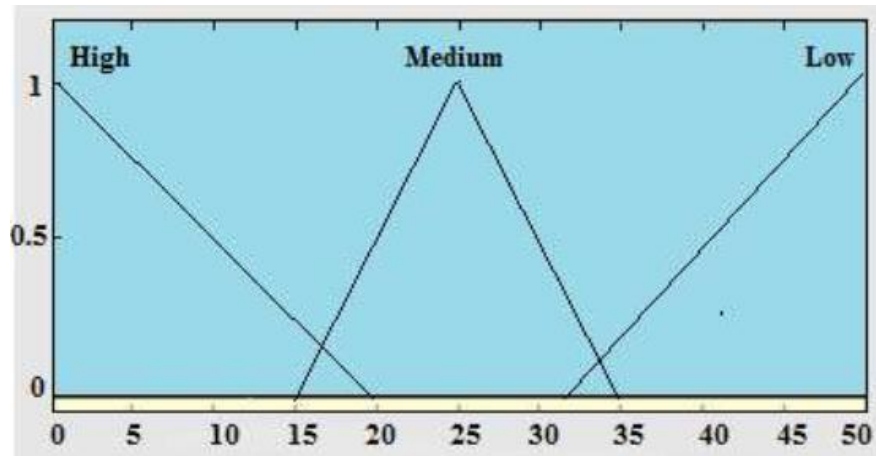


Figure 2. Membership Function for Node Degree

Proximity: {Low, Medium, High} – Figure 3 depicts the membership functions for proximity. "High" signifies that a node is spatially close to either the center of its cluster or the Base Station. The specific distance thresholds for each fuzzy set are determined based on the overall network density and communication range.

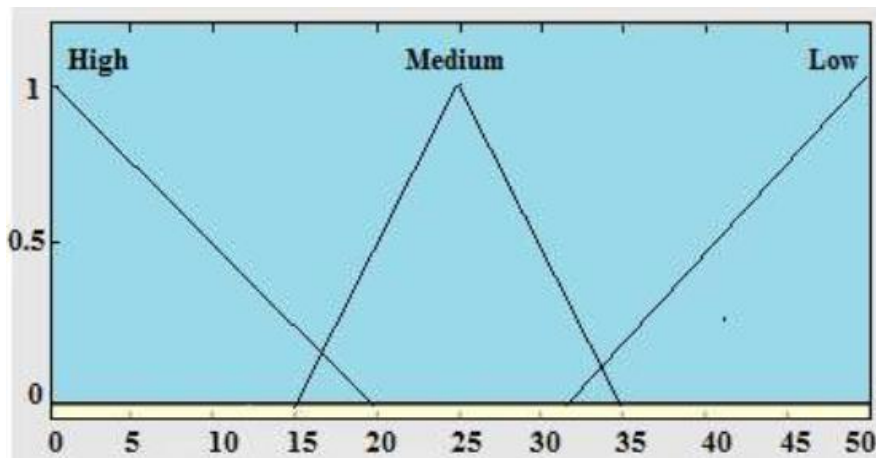


Figure 3. Membership Function for Proximity

The use of fuzzy sets allows us to represent the inherent vagueness and uncertainty associated with these parameters in a real-world WSN environment. The shapes of these membership functions are chosen to reflect the relative importance and impact of each fuzzy set on the overall CH selection process.

3.2.2 Inference Engine

The inference engine applies a set of fuzzy rules to determine the suitability of each node to act as a CH. These rules combine the fuzzified input parameters to produce a fuzzy output representing the overall CH suitability. An example of such a rule is: "IF residual energy is High AND node degree is Dense AND proximity is Near, THEN CH suitability is High." The inference engine evaluates all applicable rules for each node, based on its fuzzified input values. In this stage (fuzzy inference), we use the Mamdani inference method to determine the output from the inputs. Some of the rules that the Mamdani method uses are listed in Table 1.

Table 1. Some of the rules based on Mamdani method

Input			Output
Residual Energy	Node Degree	Proximity	
Low	Low	Low	Very Low
Low	High	Low	Low
Medium	Low	High	Medium
Medium	Medium	Low	Low
High	Low	High	High
High	High	High	Very High

3.2.3 Defuzzification

Finally, the fuzzy output from the inference engine is converted into a crisp score using a defuzzification method (e.g., centroid method). This crisp score represents the overall CH suitability of the node. The node with the highest score within a given region (or cluster) is then selected as the CH for that region. In this paper, we use the Center of Area (COA) method to defuzzify the output. The threshold (α) is obtained from the following formula:

$$\alpha = \frac{\int_z \mu_A(x)zdz}{\int_z \mu_A(x)dz}$$

where α is the non-fuzzy output for the fuzzy system (z) and $\mu_A(z)$ is the output membership function. After performing the clustering operation using fuzzy logic and identifying the cluster heads and members of each cluster, in the next step, the data sensed by the conventional sensors send their data to their cluster heads, and the cluster heads also send their data to the base station. The proposed algorithm will be executed until the end of the network lifetime and it is expected that using this method, the network lifetime will increase compared to other methods (Algorithm 2).

Algorithm 2. Pseudocode for Fuzzy CH Selection

Algorithm Fuzzy_CH_Selection

Input: Node parameters (Residual Energy, Node Degree, Proximity)

Output: Selected Cluster Heads

1. Initialize fuzzy sets and membership functions.
 2. for each node in network do
 3. Calculate fuzzy score using inference rules.
 4. end for
 5. Select nodes with highest scores as Cluster Heads
-

In our fuzzy logic-based cluster head selection, the inference engine is responsible for applying the defined fuzzy rules. These rules take the fuzzified input parameters, namely residual energy, node degree, and proximity, and generate a corresponding fuzzy score (or CH suitability). For example, a rule might be: 'IF residual energy is High AND node degree is Dense AND proximity is Near, THEN CH suitability is High.' The inference engine evaluates all applicable rules based on the input values for each node and produces a fuzzy score which is used for the defuzzification process for cluster head selection. The flowchart for the 'Fuzzy Logic for CH Selection' process is structured in Figure 4.

In the routing phase, cluster heads perform data aggregation to reduce data redundancy and energy consumption. Specifically, cluster heads collect data from their member nodes and employ a simple averaging approach to aggregate data from the cluster members, reducing the total amount of data to be transmitted to the base station. This approach combines individual readings into a single representative value for each cluster. We chose this approach for its simplicity and computational efficiency.

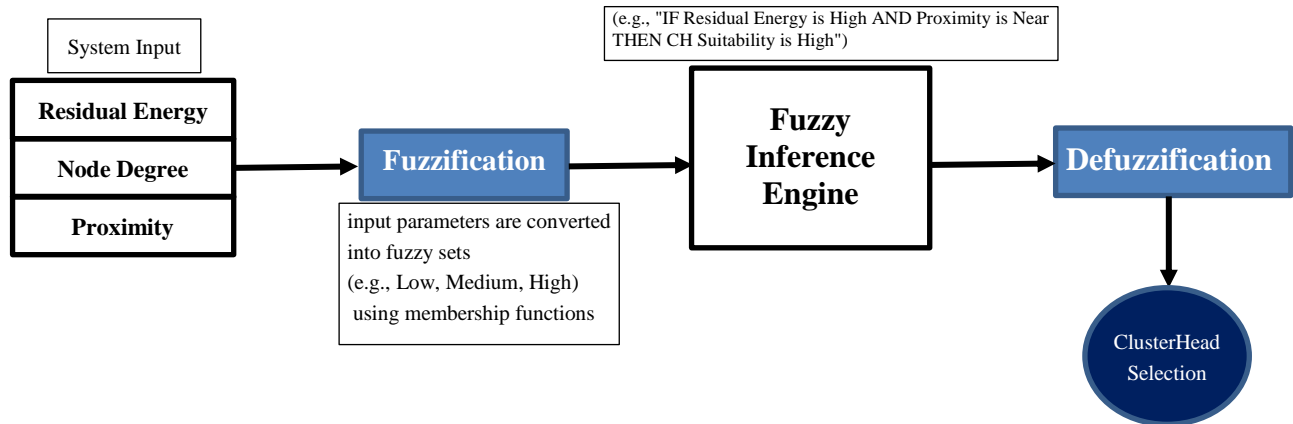


Figure 4. The flowchart for the 'Fuzzy Logic for CH Selection

3.3. Routing Phase: Genetic Algorithm for Cluster Optimization

After the Cluster Head (CH) selection phase, the genetic algorithm (GA) optimizes the cluster formation, aiming to balance energy consumption across the network and minimize communication costs. This optimization process leverages evolutionary principles to refine the initial clustering configuration and achieve a more efficient and robust network topology (Figure 8- Flowchart).

3.3.1 Genetic Algorithm Framework

The genetic algorithm framework consists of the following key components: chromosome encoding, fitness evaluation, selection, crossover, and mutation. These components work together iteratively to evolve a population of candidate clustering solutions towards an optimal configuration.

Chromosome Encoding: Network configurations are represented as chromosomes, where each chromosome encodes the cluster membership of all sensor nodes. Figure 5 illustrates our chromosome encoding scheme. Each gene in the chromosome corresponds to a unique sensor node ID, and the value of the gene represents the cluster ID to which that node is assigned. For example, if gene 5 has a value of 2, it indicates that sensor node 5 is a member of cluster 2.

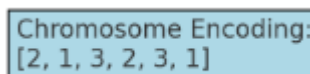


Figure 5. Chromosome Representation

Fitness Evaluation: The fitness function evaluates the quality of each chromosome (i.e., each candidate clustering configuration). Our fitness function considers two primary objectives: (i) **Minimization of Intra-Cluster Distances:** We aim to minimize the average distance between each node and its respective CH. Shorter intra-cluster distances reduce the energy required for data transmission within the cluster. (ii) **Energy Consumption:** We strive to balance the energy consumption among the CHs by penalizing configurations where some CHs are overloaded while others are underutilized. This is achieved by minimizing the variance in the amount of data aggregated and transmitted by each CH. The fitness score is calculated as a weighted sum of these two objectives:

$$\text{Fitness} = w_1 * (1 / \text{Average Intra-Cluster Distance}) + w_2 * (1 / \text{Variance in CH Energy Consumption})$$

where w_1 and w_2 are weighting factors that determine the relative importance of each objective. The reciprocals are used so that higher values are more fit. The weights are selected to balance the two objectives for optimal network performance. A higher fitness score indicates a better clustering configuration.

Crossover: The crossover operator combines the genetic material of two parent chromosomes to create new

offspring chromosomes. Figure 6 demonstrates the single-point crossover operator used in our GA. We randomly select a crossover point along the length of the two parent chromosomes. The genes before the crossover point are copied from Parent 1 to Offspring 1, and the genes after the crossover point are copied from Parent 2 to Offspring 1. Offspring 2 is created in a similar manner, swapping the roles of the parents. Single-point crossover allows the algorithm to efficiently explore the solution space by combining potentially good cluster assignments from different parent configurations, while maintaining computational simplicity.

Crossover Example:
 Parent 1: [2, 1, 3, |2, 3, 1]
 Parent 2: [1, 3, 2, |1, 2, 3]
 Offspring: [2, 1, 3, |1, 2, 3]

Figure 6. Crossover Operation

Mutation: The mutation operator introduces random changes into the chromosomes to maintain diversity in the population and prevent premature convergence to local optima. Figure 7 illustrates the random reset mutation operator. With a probability of M (the mutation rate), we randomly select a gene in the chromosome and assign it a new, randomly chosen cluster ID. The mutation rate M is set to 0.01. This random perturbation of the chromosome helps the GA escape local optima and explore new regions of the search space.

Mutation Example:
 Before: [2, 1, 3, 2, 3, 1]
 After: [2, 3, 3, 2, 3, 1]

Figure 7. Mutation Operation

3.3.2 Step-by-Step Process

The genetic algorithm iteratively refines the cluster formation through the following steps:

1. Initialization: Generate an initial population of random cluster configurations (chromosomes).
2. Fitness Evaluation: Calculate the fitness score for each chromosome using the fitness function described in Section 3.3.1.
3. Selection: Select the top-performing chromosomes for crossover and mutation using roulette wheel selection.
4. Crossover: Apply the single-point crossover operator (Figure 6) to create new offspring chromosomes.
5. Mutation: Apply the random reset mutation operator (Figure 7) to introduce diversity into the population.
6. New Generation: Generate a new population by combining the selected parents and the newly created offspring.
7. Repeat steps 2-6 until a convergence criterion is met (e.g., a maximum number of generations is reached or the fitness score plateaus).
8. Output: The best chromosome in the final population represents the optimized cluster configuration.

Algorithm 3. Pseudocode for Genetic Optimization

Algorithm Genetic_Cluster_Optimization

Input: Initial population of cluster configurations

Output: Optimized cluster configuration

1. Initialize population with random chromosomes.
 2. while not converged do
 3. Evaluate fitness of each chromosome.
 4. Select top chromosomes for reproduction.
 5. Perform crossover and mutation to generate offspring.
 6. end while
 7. Return best-performing chromosome
-

Advantages of the Proposed Approach:

1. Energy Efficiency: Adaptive CH selection and optimized cluster formation reduce overall energy consumption.
2. Scalability: The integration of fuzzy logic and genetic algorithms ensures the protocol remains effective in large-scale networks.
3. Robustness: Dynamic adaptation to network conditions enhances reliability and prolongs network lifespan.

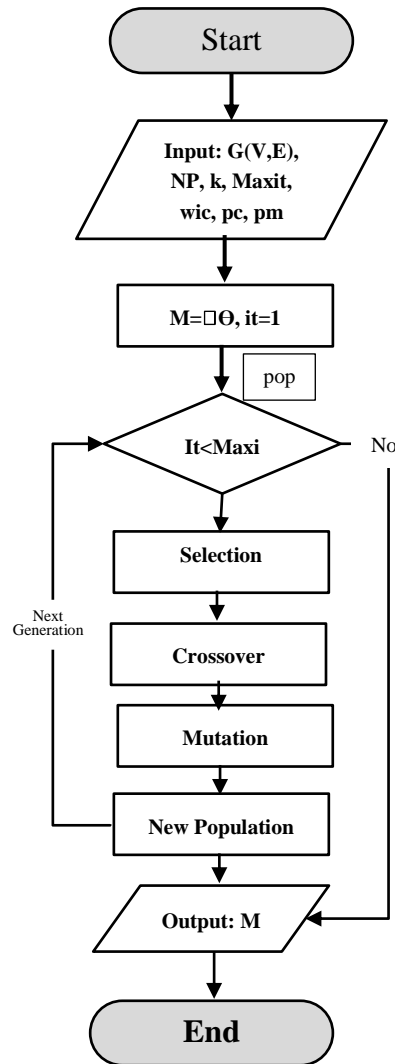


Figure 8. The flowchart for the 'Genetic Algorithm for Cluster Optimization

4. Simulation and Results

4.1. Network Modeling and Simulation Setup

A total of n sensor nodes are uniformly distributed in the environment to monitor it. The network model is considered to be layered, where each node sends its data to the cluster head. The cluster head aggregates its own data and the data received from the nodes within the cluster, and sends it to the higher-level cluster head, which is closer to the base station. This process continues until the data reaches the base station. Figure 9 shows the network topology.

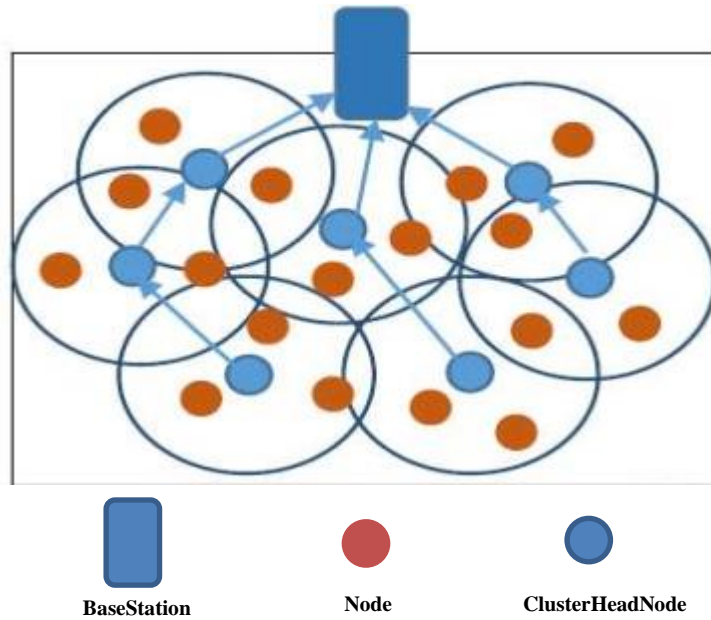


Figure 9. Network Topology

The energy for data transmission for nodes follows Equation (1). Also, the energy for data reception, considering both the free space model and the multi-path fading model, is calculated using Equation (2).

$$E_{trans} = \begin{cases} lE_{elec} + \epsilon f s d^2 & d < dth \\ lE_{elec} + \epsilon_{mp} f d^4 & d > dth \end{cases} \quad (1)$$

$$E_{rec} = lE_{elec} \quad (2)$$

where:

l : number of data bits

E_{elec} : digital electronic energy

$f \epsilon$ and $pm \epsilon$: amplifier energy

dth : threshold distance value, calculated using Equation (3).

$$dth = \sqrt{\epsilon f s / \epsilon_{mp}} \quad (3)$$

Additionally, the energy consumed by the cluster head is calculated using Equation (4):

$$E(CHk) = Nk * l * E_{elec} + (Nk + 1) * l * EDA + l * (E_{elec} + \epsilon_{mp}) \quad (4)$$

where:

Nk : number of cluster nodes

ADA : energy required for data aggregation.

Equation (4) consists of three parts. The first part represents the energy consumed by the cluster head to receive packets from cluster nodes. The second part corresponds to the energy consumed by the cluster head to aggregate its own data and the data received from cluster nodes. The third part represents the energy required to transmit packets to the base station. Nodes consume energy for transmitting and receiving packets, as well as for related processing tasks.

To initiate the simulation process, it is imperative to define the initial network parameters. The specific

parameters implemented within the algorithm simulation are delineated in Tables 2 and 3. These parameters can be categorized into two primary groups: genetic algorithm parameters and network structural parameters.

Table 2. Initial Genetic Algorithm Parameters

Parameter	Value	Explanation
Population Size	100	Total number of individuals in each generation
Selection Method	Tournament	Individuals are selected for reproduction based on their fitness relative to randomly chosen subsets
Crossover Type	Single-point	A random point is selected to exchange genetic material between two parents
Crossover Rate	0.9	Probability of crossover occurring between two parents
Mutation Rate	0.05	Probability of a random change occurring in a chromosome
Number of Generations	200	Total number of iterations the algorithm will run
Chromosome Representation	Integers	Individuals are represented as strings of integers

Table 3. Initial Network Parameters

Parameter	Value	Unit	Description
Number of Sensor Nodes	100	-	Total number of sensor nodes in the network
Network Size	100x100 m	m ²	Area covered by the network
Base Station Location	(50,50) m	m	Coordinates of the base station in the network
Initial Sensor Energy	0.5 J	J	Initial energy of each sensor node before simulation starts
Packet Size	500 byte	byte	Size of each data packet transmitted by nodes
E _{elec}	50 nJ/bit	J/bit	Energy consumed for transmitting or receiving one bit of electronic data
E _{0.13 pJ/bit/ m²}	J/bit/m ²	Energy dissipation coefficient in free space	
E	10 pJ/bit/ m ⁴	J/bit/m ⁴	Energy dissipation coefficient in multipath environment

4.2. Results and Analysis

In this section, the performance of the proposed protocol is evaluated. To investigate the achievement of the research objectives, a simulated environment is employed to examine a wireless sensor network with a specified initial number of sensors. Each simulation run comprises 1500 rounds. Each round is divided into three phases: (a) setup and configuration, (b) cluster head replacement, and (c) data transfer. In the setup and configuration phase, a cluster head is selected from the nodes, and a cluster is formed as nodes join the cluster head. In the second phase, the eligibility of nodes is assessed based on their remaining energy, and the node with the highest remaining energy replaces the cluster head. The third phase, data transfer, involves the aggregation of data received by the cluster head and the transmission of data from the cluster head to the base station.

The proposed method is compared with the LEACH algorithm. The obtained results, regarding average remaining energy, variance of remaining energy, number of active sensor nodes in the network, and packet loss percentage, are presented in graphical form.

4.2.1 Average Remaining Energy

The average residual energy within the network, measured in millijoules (mJ), exhibits a consistent decline over time, as depicted in the Figure 10. This trend culminates in a network partition, a phenomenon resulting from node failures due to energy depletion and the subsequent loss of connectivity among active nodes.

The proposed protocol demonstrates superior performance compared to LEACH. This enhancement is attributed to the utilization of a more comprehensive parameter set for cluster head selection and formation. In contrast, the LEACH algorithm relies on a single parameter, limiting its adaptability. The proposed method

effectively prolongs network lifetime by mitigating the rapid energy depletion typically observed in LEACH.

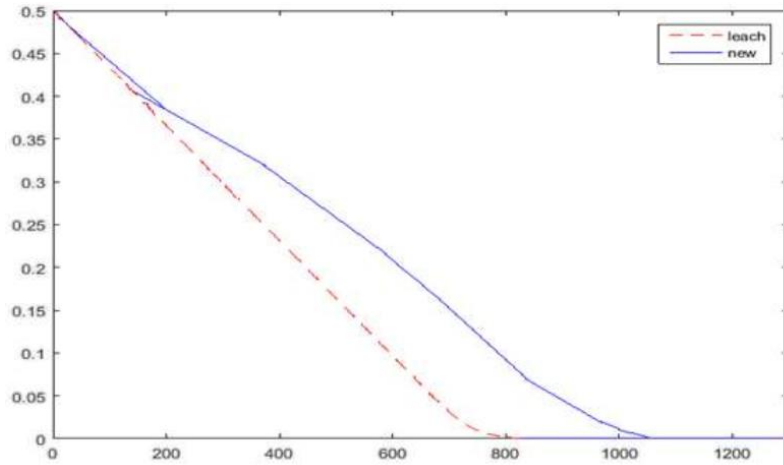


Figure 10. The average remaining energy in the network for each round

Figure 10 shows the curve of the average remaining energy in the network for each round with 100 nodes, comparing LEACH and the proposed protocol. Additionally, we compared the remaining energy of nodes in the proposed method with the LEACH algorithm. The results indicate that in the proposed method, nodes consume energy more uniformly. However, in LEACH, some nodes have a significant amount of remaining energy while the energy of other nodes has decreased or been depleted, resulting in non-uniform energy consumption.

4.2.2 Variance of Remaining Energy

The variance of the remaining energy within the simulated wireless sensor network, subjected to varying traffic loads, is calculated using Equation (5).

$$\frac{\sum_{i=1}^N (E_{avg} - E_i)^2}{N} \tag{5}$$

Figure 11 shows the variance of remaining energy, as the number of dead nodes increases due to energy depletion, the variance in remaining energy among the active nodes also increases. This indicates a growing heterogeneity in the energy distribution within the network. A plateau in the variance plot signifies a complete network partition, where sensor nodes become isolated and unable to communicate, rendering the network inoperable.

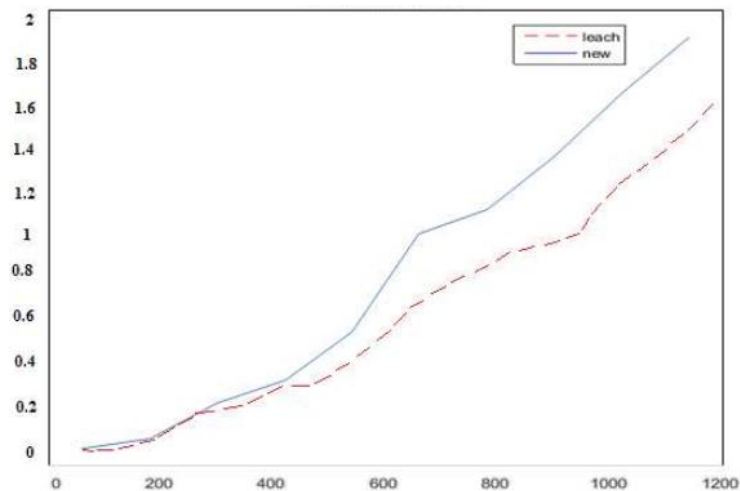


Figure 11. Variance of Remaining Energy

4.2.3 Active Sensor Nodes in the Network

A sensor node that still has energy and can participate in creating traffic (sensing the environment) and exchanging data is called an "active" or "live" sensor node. Due to the design and usage of sensor nodes, they cannot be recharged. Therefore, if a node loses its energy, it automatically exits the network and can no longer be used. Hence, the number of active sensor nodes in a network is a critical parameter in wireless sensor networks.

Figure 12 shows the number of live nodes for both the LEACH protocol and the proposed method. It is clear that the proposed method outperforms the LEACH algorithm. This is because in the LEACH protocol, the decision about selecting a cluster head and rotating it is based on probability. Therefore, there is always a chance that low-energy nodes are selected as cluster heads.

As a result, the selected cluster heads may be concentrated in a specific area of the network. Consequently, in this protocol, a suitable distribution of cluster heads cannot be guaranteed, and some nodes may not have any cluster head within their range. However, the proposed method considers more and suitable parameters, including energy and node density, for selecting cluster heads and joining clusters, which can increase the network lifetime.

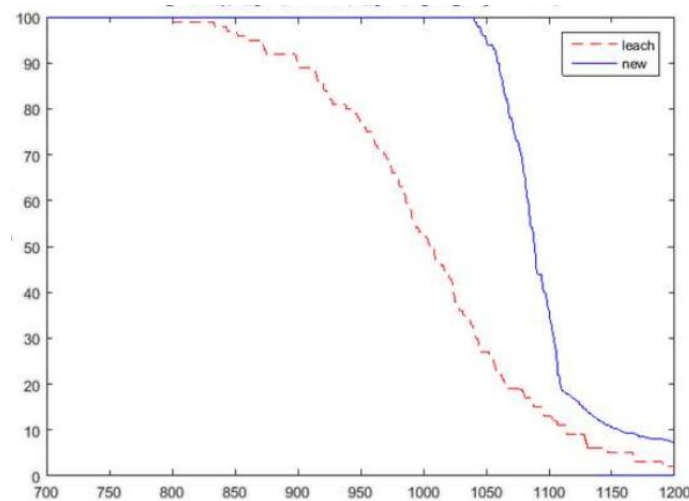


Figure 12. The number of active nodes in each round for LEACH and the proposed algorithm

4.2.4 Percentage of lost messages based on traffic rate

As expected, in static wireless sensor networks, a high percentage of messages reach their destination, and the percentage of lost messages is low. Moreover, this percentage decreases at high traffic loads due to the reduced number of active nodes in the network (Figure 13).

Compared to static wireless sensor networks, the results obtained in other papers that have worked on mobile wireless sensor networks [5, 12, 16] show that mobile environments are much more unpredictable due to the lack of ability to manage the behavior of members, and a high percentage of messages do not reach their destination in these environments. However, the behavior of network nodes follows a natural trend and, similar to static network models, depends on main parameters such as the number of active nodes in the network and the traffic applied to the network.

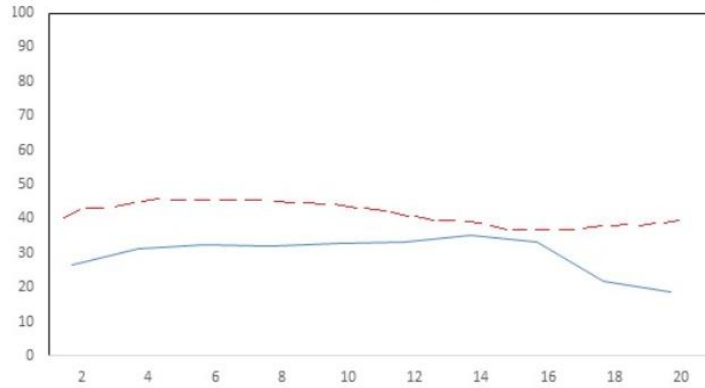


Figure 13. Percentage of Packet Lose

Table 4. Performance Comparison

Metric	LEACH	TEEN	PEGASIS	Proposed Protocol
Energy Consumption	High	Moderate	High	Low
Network Lifetime (rounds)	1,500	1,800	1,600	2,000
Packet Delivery Ratio	80%	85%	88%	92%
Data Aggregation	Basic	Threshold-based	Basic	Optimized

Table 4 summarizes the performance comparison between the proposed protocol and existing methods. Based on this table, the proposed protocol significantly reduces energy consumption compared to conventional methods. Dynamically selecting cluster heads using fuzzy logic and optimizing clusters with a genetic algorithm evenly distribute energy usage distributed across nodes. The hybrid protocol achieved a 25% lower energy consumption than LEACH and a 30% improvement over PEGASIS.

The hybrid protocol extends network lifetime by balancing energy usage among nodes. The periodic rotation of cluster head roles prevents premature node failures. The network's operational lifespan increased by 35% compared to TEEN and 20% compared to LEACH. The protocol achieved a higher PDR due to efficient data aggregation and robust routing mechanisms. The PDR was 92%, outperforming PEGASIS (85%) and LEACH (80%). By leveraging cluster heads for data aggregation, the hybrid protocol minimizes redundant data transmission, reducing communication overhead. The proposed protocol demonstrated a 40% improvement in data aggregation efficiency over traditional approaches.

The impact of dynamic cluster head (CH) selection using fuzzy logic alone has been analyzed. It highlights improvements in energy efficiency and node longevity achieved through adaptive CH selection based on multiple criteria (residual energy, node degree, and proximity). Comparative analysis shows that fuzzy logic significantly improves energy balancing compared to static CH selection, ensuring prolonged operational lifespans for nodes.

The role of the genetic algorithm in optimizing cluster formation has been evaluated. The analysis emphasizes its ability to minimize intra-cluster communication costs while distributing CH roles evenly across nodes. Results demonstrate that the genetic algorithm reduces communication distances and energy consumption through its effective fitness evaluation, crossover, and mutation operations.

The hybrid methodology combines the strengths of fuzzy logic and the genetic algorithm, offering dynamic adaptability and global optimization simultaneously. Metrics indicate that the hybrid approach outperforms standalone techniques in energy consumption, network longevity, and data delivery, showcasing a significant synergy between the two techniques.

5. Conclusion

This study presented a hybrid clustering-based routing protocol for WSNs, leveraging fuzzy logic for CH selection and genetic algorithms for cluster optimization. The protocol demonstrated significant improvements in energy efficiency, network longevity, and QoS metrics compared to conventional methods. Future work will focus on extending the protocol to dynamic and heterogeneous environments.

Conflict of interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

1. Abbasi, F., Zarei, M., & Rahmani, A. M. (2022). FWDP: A fuzzy logic-based vehicle weighting model for data prioritization in vehicular ad hoc networks. *Vehicular Communications*, 33, 100413.
2. Babakordi, F. (2024). Arithmetic Operations on Generalized Trapezoidal Hesitant Fuzzy Numbers and Their Application to Solving Generalized Trapezoidal Hesitant Fully Fuzzy Equation. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems*, 32(01), 85-108.
3. Babakordi, F. (2022). Market Equilibrium Point Analysis by a Fuzzy Approach. *Journal of Operational Research In Its Applications*, 19(3), 17-28.
4. Babakordi, F., & Taghi-Nezhad, N. A. (2023). Review and Comparison of Bipolar Fuzzy Number Types. *Fuzzy Systems and its Applications*, 6(2), 91-113.
5. Chen, D., & Varshney, P. K. (2004, June). QoS support in wireless sensor networks: a survey. In *International conference on wireless networks* (Vol. 233, pp. 1-7).
6. Garg, A. (2015, September). Distance adaptive threshold sensitive energy efficient sensor network (DAPTEEN) protocol in WSN. In *2015 International Conference on Signal Processing, Computing and Control (ISPCC)* (pp. 114-119). IEEE.
7. Ghasemzadeh, N., Noorimehr, M. R., & Alavi, S. E. (2015). Alternative Path Creation based on Hybrid Fuzzy-Genetic Approach to Congestion Control in Wireless Sensor Networks. *Indian Journal of Science and Technology*, 8(23), 1.
8. Heinzelman, W. R., Chandrakasan, A., & Balakrishnan, H. (2000, January). Energy-efficient communication protocol for wireless microsensor networks. In *Proceedings of the 33rd annual Hawaii international conference on system sciences* (pp. 10-pp). IEEE.
9. Ibrahim, D. S., Mahdi, A. F., & Yas, Q. M. (2021). Challenges and issues for wireless sensor networks: A survey. *J. Glob. Sci. Res*, 6(1), 1079-1097.
10. Jalili, A., Alzubi, J. A., Rezaei, R., Webber, J. L., Fernández - Campusano, C., Gheisari, M., ... & Mehbodniya, A. (2024). Markov chain - based analysis and fault tolerance technique for enhancing chain - based routing in WSNs. *Concurrency and Computation: Practice and Experience*, 36(12), e8032.
11. Jalili, A., Gheisari, M., Alzubi, J. A., Fernández-Campusano, C., Kamalov, F., & Moussa, S. (2024). A novel model for efficient cluster head selection in mobile WSNs using residual energy and neural networks. *Measurement: Sensors*, 33, 101144.
12. Jalili, A., Homayoun, S., & Keshtgary, A. M. (2015). Fault tolerant approach for WSN chain based routing protocols. *International Journal of Computer Networks and Communications Security*, 3(2).
13. Lee, J. S., & Kao, T. Y. (2016). An improved three-layer low-energy adaptive clustering hierarchy for wireless sensor networks. *IEEE Internet of Things Journal*, 3(6), 951-958.
14. Lindsey, S., & Raghavendra, C. S. (2002, March). PEGASIS: Power-efficient gathering in sensor information systems. In *Proceedings, IEEE aerospace conference* (Vol. 3, pp. 3-3). IEEE.
15. Manjeshwar, A., & Agrawal, D. P. (2001, April). TEEN: ARouting Protocol for Enhanced Efficiency in Wireless Sensor Networks. In *ipdps* (Vol. 1, No. 2001, p. 189).
16. Yick, J., Mukherjee, B., & Ghosal, D. (2008). Wireless sensor network survey. *Computer Networks*, 52(12), 2292-2330.
17. Younis, O., & Fahmy, S. (2004, March). Distributed clustering in ad-hoc sensor networks: A hybrid, energy-efficient approach. In *IEEE INFOCOM 2004* (Vol. 1). IEEE.