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Energy-Aware Clustering Using Intelligent Scheme for Heterogeneous Wireless Sensor Networks

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Keywords

Cluster Heads; Heterogeneous WSN; IT2-Fuzzy Logic; Network Performance; Castalia; OMNET++.

RESEARCH PAPER

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Heterogeneous Wireless Sensor Networks (WSNs) involve nodes with varying capabilities, such as different energy levels, sensing ranges, and computational abilities, which enable them to execute different tasks professionally. Clustering techniques play a crucial role in improving energy efficiency and reliability in WSNs. The evolution of cluster based WSNs from homogeneous to heterogeneous techniques allowed the deployment of smart devices capable of performing complex operations in diverse environments. However, the heterogeneity of nodes necessitates more sophisticated and adaptive algorithms to fully exploit these capabilities. This paper proposes a new protocol, referred to as IT2F-HLEACH, which integrates Interval Type-2 Fuzzy Logic (IT2-FL) to address uncertainties in decision-making processes. The protocol dynamically adjusts the clustering decisions by considering network conditions and the capabilities of individual nodes. Besides, the proposed protocol is designed for two distinct heterogeneous network scenarios: The Two-Level Heterogeneous Scenario and the Three-Level Heterogeneous Scenario. Simulation results obtained using the Castalia simulator with OMNeT++ demonstrate that the recommended protocol significantly prolongs network lifetime, reduces energy consumption, and improves data transmission. The findings indicate that the proposed protocol outperforms the SEP protocol regarding First Node Dead (LND) and Last Node Dead (LND) with initial energy equal to 3 J by 321.82 % and 36.66 %, respectively. While, the proposed protocol outperforms the EEHC protocol in terms of FND and LND by 235.71 % and 71.95 %, respectively. This result may be explained by the fact that the lifespan of the IT2F-HLEACH protocol is significantly longer in the two suggested heterogeneous scenarios than SEP and EEHC, resulting in a significant increase in the amount of data transmitted to the sink node.

Keywords: Cluster heads, Heterogeneous WSN, IT2-Fuzzy Logic, Network performance, Castalia, OMNeT++

1. Introduction

With improvements in micro-electromechanical systems (MEMS) and wireless modern technology, inventors are concentrating on many intelligent applications such as IoT, Cloud Computing, and Big Data Analytics [1]. Wireless Sensor Networks (WSNs) are an underlying infrastructure in many wireless-based intelligent applications that engendered seamless connectivity, data collection, and analysis in diverse environments. It includes several specialized sensors that are used in a variety of applications, including environment sensing, disaster forecasting and management, environment monitoring, automated transportation, military surveillance, and weapon management [2,3]. Clustering involves identifying inherent connections among items and classifying them [4]. Accordingly, the cluster based WSN divides the entire collection of Sensor Nodes (SNs) into sets/clusters. Each cluster has many nodes named Member Nodes (MNs) and one Cluster Head (CH). The MNs generate data packets and exclusively communicate with the CH which gathers the received data and retransmit it to the Base Station (BS) [5,6]. Thus, the clustering strategy ensures that long-range communication responsibilities depend on a limited number of nodes. Furthermore, it permits data aggregation, which further conserves the energy of the communicated nodes.

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Utilizing heterogeneity in WSNs is crucial for improving the performance and capabilities of the network. Employing various SNs with different energy levels and transmission ranges enhances security, conserves power, and enhances packet delivery by decreasing end-to-end delay time in WSNs. While clustering technology in heterogeneous WSNs can address numerous difficulties, it results in more efficient energy usage, increased network reliability, prolonged network lifespan, and improved coverage and performance through collaborative sensor node communication. Different clustering protocols (SEP, DEEC, HEED & PEGASIS) have been suggested to implement a heterogeneous network in WSNs, demonstrating the advantages of models with heterogeneity in terms of stability, throughput, remaining energy, and lifetime performance. Properly implemented heterogeneity is crucial for the long-term viability of the existing WSNs, supporting their ability to excel in a wide range of areas such as IoT, smart cities, healthcare services, and more [7,8].

Low Energy Adaptive Clustering Hierarchy (LEACH) [9] is a revolutionary clustering routing protocol for WSNs that aims to enhance energy efficiency by randomly selecting Cluster Heads (CHs). The protocol operates in rounds, with two distinct phases: Set-Up and Steady-State. In the Set-Up phase, clusters are formed, and a CH is elected for each cluster. In the Steady-State phase, data is detected, aggregated, compressed, and transmitted to the base station (BS). Despite the fact that LEACH preserves sensor node energy, it has several limitations such as:

1. Cluster formation that is not uniform due to randomness.
2. Insufficient centralized management to achieve ideal cluster development.
3. Scalability is limited by network size.
4. Heterogeneity in energy computational capabilities and link reliability are not considered.
5. A static cluster formation may not be flexible enough to accommodate changes.
6. Limited support for mobile nodes.
7. Security vulnerabilities.
8. Selection of cluster head acquires overhead.
9. Limited support for Quality of Service (QoS) requirements.

Hence, numerous smart optimization methods are utilized to tackle the challenges of LEACH by handling incomplete information and striving for approximate yet satisfactory solutions to enhance performance.

However, researchers have highlighted the significance of Fuzzy Logic (FL) as a key element in enhancing decision-making for WSNs' CH performance. These smart and scalable methods utilize FL to effectively distribute the workload among the SNs, and enhance the network's lifespan. Significant advancements have been achieved by researchers in CH selection algorithms through the application of the T1-Fuzzy Logic System. The algorithms utilize various important parameters, like the distance to the Base Station (BS) and remaining energy, as input factors for the fuzzy inference system [10−12]. This allows the system to determine the best solution for choosing appropriate Cluster Heads (CHs) and creating clusters.

Although using a T1-Fuzzy system to optimize routing protocols is commonly viewed as an effective method, the Type-1 Fuzzy system has limitations when it comes to handling significant levels of uncertainty in selecting CHs, as outlined below:

1. Input uncertainties in Fuzzy Inference Systems (FIS) can arise due to several factors, including high levels of noise that can affect the sensor readings.
2. Control outputs uncertainties due to changes in the system characteristics resulting from regular usage, environmental factors, and other related factors.

Thus, to improve the selection of CHs, it may be necessary to evaluate a larger number of criteria. This, in turn, highlights the need for a clustering system that can effectively handle high levels of uncertainty. As a result, the development of a clustering system that is capable of handling significant levels of uncertainty is required. To the best of our knowledge, the heterogeneous energy distribution of each sensor in conjunction with the IT2 fuzzy approach has not been addressed in the literature. Hence, to optimize Quality of Service (QoS) performance, this paper introduces a novel approach named “Interval Type-2 Fuzzy based Heterogeneous LEACH (IT2F-HLEACH.” This approach leverages the IT2-FLC model as an authoritative tool for determining the optimal number of Cluster Heads (CHs). The study also investigates the impact of node heterogeneity on energy consumption, since homogeneous clustering methods assume that all sensor nodes have equal amounts of energy, which limits their ability to utilize node heterogeneity. Hence, an adaptive energy-efficient heterogeneous clustering system for WSNs is proposed in this paper, which uses weighted election probabilities of each sensor node based on its residual energy along with IT2-Fuzzy output to select the cluster Head (CH).

Consequently, the main contributions of this study can be summarized as:

1. A new IT2 Fuzzy-based clustering protocol has been introduced to improve the Quality of Service (QoS) parameters of WSNs, with a specific concentration on heterogeneous networks.
2. The integration of IT2-Fuzzy Logic with heterogeneous cluster based protocol eliminates the limitations of the heterogeneous WSN by improving the selection process for cluster heads, enabling the consideration of multiple criteria for better decision-making.
3. The suggested approach includes essential criteria for choosing a CH effectively, which can have significant impacts on the network's overall performance. The effectiveness of the suggested strategy is demonstrated by comparing it to other heterogeneous clustering methods in WSNs, using metrics like energy efficiency, network lifetime, and data transmission rates.
4. The research contributes to the advancement of clustering methods in WSNs, especially in situations necessitating effective energy control and extended network lifespan. The technique may be particularly beneficial in many fields such as environmental surveillance, where sustaining energy is necessary.

The rest of this paper is organized into seven subsequent sections. Firstly, Section 2 discusses the previous related works that identify the technical deficiencies that inspired the development of the suggested protocol. Then, Section 3 provides a detailed description of the proposed IT2-fuzzy control system. Section 4 presents the network model. Meanwhile, in Section 5, the suggested protocol, including its protocol architecture, operational phases, and the algorithm is analyzed. Additionally, Section 6 discusses simulation experimentation, demonstrating the superiority and validity of the proposed protocol compared to existing ones across various network configurations. Finally, Section 7 presents the conclusion illustrated from the study.

2. Related works

Many researchers have suggested various algorithms and techniques to enhance the selection of cluster heads based on these factors, aiming to improve network performance and prolong the network lifetime of WSNs.

For heterogeneous WSNs, T. Shafique et al. [13] suggested a data traffic-based, shape-independent, adaptive unequal clustering approach. Their method includes data flow patterns in the clustering process which yield adaptable cluster configurations according to these different network scenarios. S. NagaMallik Raj et al. [14] introduced the Low Energy Utilization with Dynamic Cluster Head (LEU-DCH) protocol to reduce energy consumption in WSNs. The protocol optimizes energy efficiency and prolongs network lifetime by dynamically selecting cluster heads based on the remaining energy on the nodes. Additionally, A. H. Abdulaal et al. [15] introduced NM-LEACH, an altered form of the traditional LEACH protocol. Generally, implementing their improvements reduces general performance metrics such as network lifespan and data transmission rates. The continuous improvement of the clustering protocols is shown with NM-LEACH having improved energy efficiency by overcoming standard LEACH limitations.

The authors in Refs. [16−22] suggest various optimization algorithms to effectively reduce energy usage in WSNs and prolong the network's lifespan. In particular, some recent works have suggested neuro-fuzzy and deep learning techniques to improve the cluster-based routing protocol. For instance: The authors in Ref. [23] introduce a Swarm Intelligence with Adaptive Neuro-Fuzzy Inference System-Based Routing Protocol for Clustered Wireless Sensor Networks, increasing energy efficiency and network lifetime through intelligent routing techniques; F.M. A-Matarneh et al. [24] introduce the Neuro-fuzzy model which is used for data prediction in Passive Clustered Wireless Sensor Networks in order to reduce mean square error and improve energy efficiency with node predictions.

Furthermore, authors in Refs. [25,26] provide a cluster-based system that combines neural networks and deep learning for optimal data transmission. They also include a unique routing analysis methodology for effective routing decisions.

However, many research studies proposed the use of fuzzy systems to dynamically adjust the selection of the cluster heads in terms of traffic patterns and real-time network conditions to achieve a more adaptive and responsable way to maximize network performance. Specifically, A. K. Dwivedi and A. K. Sharma [27] introduced FEECA, a clustering method based on fuzzy logic designed to progress the energy efficiency of WSNs. Cluster formation in the protocol is adapted dynamically by using the protocol which employs the fuzzy logic to increase network lifespan and reduces the energy usage. Additionally, several Cluster Head (CH) election algorithms based on Type-1 Fuzzy Logic (T1-FL) have been proposed by the authors in Refs. [28−31].

To determine the best course of action for choosing suitable CHs, these algorithms make use of a variety of effective parameters as input to the fuzzy inference system, such as residual energy and distance to the Base Station (BS). Notably, as highlighted in the literature, a few studies such as [32,33] have proposed the use of Interval Type-2 Fuzzy Logic (IT2-FL) rather than the Type-1 Fuzzy Logic (T1-FL) model as an effective method of selecting uncertain levels. In these works, a fuzzy-based cluster head election technique is proposed by the authors for balancing energy efficiency protocols. In the meantime, according to Refs. [34,35], the authors employed an IT2-FL model that fed a Fuzzy Inference System (FIS) with information about node density, centrality, distance from the base station, and residual battery power. Simulation results showed that the performance of these approaches as superior to other the clustering algorithms studied with respect to network lifetime and throughput. However, these protocols did not take into consideration sensor heterogeneity and mobility. A comprehensive overview of most recent studies with limitation is presented in Table 1.

Upon these, in this work, an IT2-Fuzzy Logic-based unequal clustering scheme is suggested to assist sensor heterogeneity along with cluster selection and formation randomization. Additionally, realistic simulators such as OMNeT++ and Castalia are considered. They provide robust simulation and analysis of the most real WSN parameters.

3. Proposed IT2−Fuzzy control system

IT2-FS operates as a powerful scheme for dealing with uncertain scenarios through different applications including identification patterns and system regulation together with decision processes. While managing imprecise and imprecise information, they have an advantage over Type-1 fuzzy systems due to their unique capacity to capture both main and secondary uncertainty. The interval type-2 fuzzy inference system is composed of five stages as illustrated in Refs. [36,37]. These stages can be visualized in Fig. 1.

Our proposal for the IT2-FIS includes three inputs and one output as follows:

1. **The Residual Energy of Sensor Node:** Cluster Heads (CHs) are essential for communication between member nodes and the Base Station (BS) in a large-scale Wireless Sensor Network (WSN) made up of non-rechargeable sensor nodes (SNs). A node's

Residual Energy (REN) metric decides whether a node becomes a CH while selecting nodes with greater REN scores. The REN of a sensor node ‘i’ is calculated as follows:

Table 1. Literature review of fuzzy based clustering protocols.

First Author	Suggested Protocol	Simulation Environment	Advantages	Limitations
A. K. Dwivedi *et.al.* [27]	FEECA	MATLAB	1. Prolonged network lifespan. 2. Upgraded energy efficiency. 3. Improved stability.	1. Scalability. 2. Implementation complexity. 3. Diagonal division.
S. Lata *et. al.* [28]	LEACH-FC	MATLAB	1. Improved reliability. 2. Reduced energy depletion.	1. Computational overhead. 2. Sensitivity to parameter settings. 3. Lack of scalability.
D. Agrawal *et.al.* [29]	HS_Fuzzy	MATLAB	1. Optimized CH selection. 2. Hot-spot issue resolution.	1. Computational complexity. 2. Generalization.
P. K. Batra *et. al.* [30]	FL-SEP and FL-SEP-E	MATLAB	1. Extended network lifetime. 2. Energy efficiency.	1. Complexity. 2. Real-world implementation.
L. Yang *et. al.* [31]	SCFTO	Not mentioned	1. Enhanced security. 2. Upgraded reliability.	1. Computational overhead. 2. Scalability.
A. Kousar *et. al.* [32]	LEACH-MT2FL	MATLAB	1. Handling uncertainty. 2. Enhanced adaptability. 3. Improved energy efficiency.	1. Scalability issues. 2. Mobility impact. 3. Homogeneous WSN.
E. A. Al-Husain *et. al.* [33]	EEIT2-F LEACH	MATLAB	1. Energy efficiency. 2. Handling uncertainty. 3. Network scalability.	1. Homogeneous WSN. 2. Overhead in CH selection. 3. Computational complexity.
M. Adnan *et. al.* [34]	Not mentioned	MATLAB	1. Energy efficiency. 2. Improved decision making. 3. Improves scalability.	1. Computational complexity. 2. Overhead according to multi-hop nature.
Y. Tao *et. al.* [35]	UCT2TSK	MATLAB	1. Energy efficiency. 2. Robustness. 3. Improved data transmission.	1. Complexity. 2. Scalability.

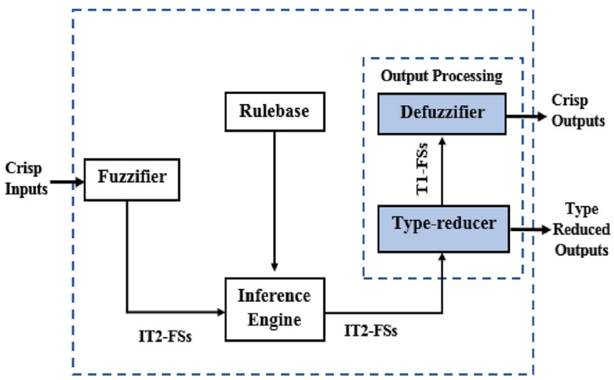

Fig. 1. Typical structure of the IT2 FIS.

$$REN = Initial\ Energy\ \text{-}\ Consumed\ Energy. \tag{1}$$

2. **Node Distance from the BS:** Data transmission, especially over long distances, is the most energy-intensive operation in a sensor node (SN). As a result, choosing a CH that is closer to the Base Station (BS) uses less energy when transmitting aggregated data. Any sensor node (x, y) can calculate its Euclidean distance 'd' to the base station through this formula:

$$distance = \sqrt{(x_{Node} - x_{BS})^2 + (y_{Node} - y_{BS})^2} \tag{2}$$

3. **Node Centrality:** Node centrality defines the cumulative distances from neighboring SNs within a specified range 'R' of the node.

Our IT2-FIS in this proposed approach employs three input variables: REN (Low, Medium, High), DBS (Close, Average, Far), and CEN (Little, Appropriate, Distant) to determine the probability (Chance) of a sensor node becoming a CH. To facilitate this, trapezoidal membership functions are applied to the input linguistic variables, as visually represented in Fig. 2. Since each input parameter is divided into three levels, the system encompasses 27 rules.

Tables 2 and 3 describe the linguistic variables for both input and output membership functions (MFs), along with the output MF intervals, while Table 4 provides a comprehensive listing of the 27 rules employed in the system.

4. Network model

The proposed network model comprises a set of stationary sensor nodes (N) distributed across a designated area with dimensions (M x M), with the base station (BS) located at the center of the sensor field. These nodes are equipped with the capability to sense, collect, and transmit data to the sink node, serving as the base station (BS). Additionally, all sensor nodes within the field of interest (FoI) are non-rechargeable. Furthermore, the sensor nodes

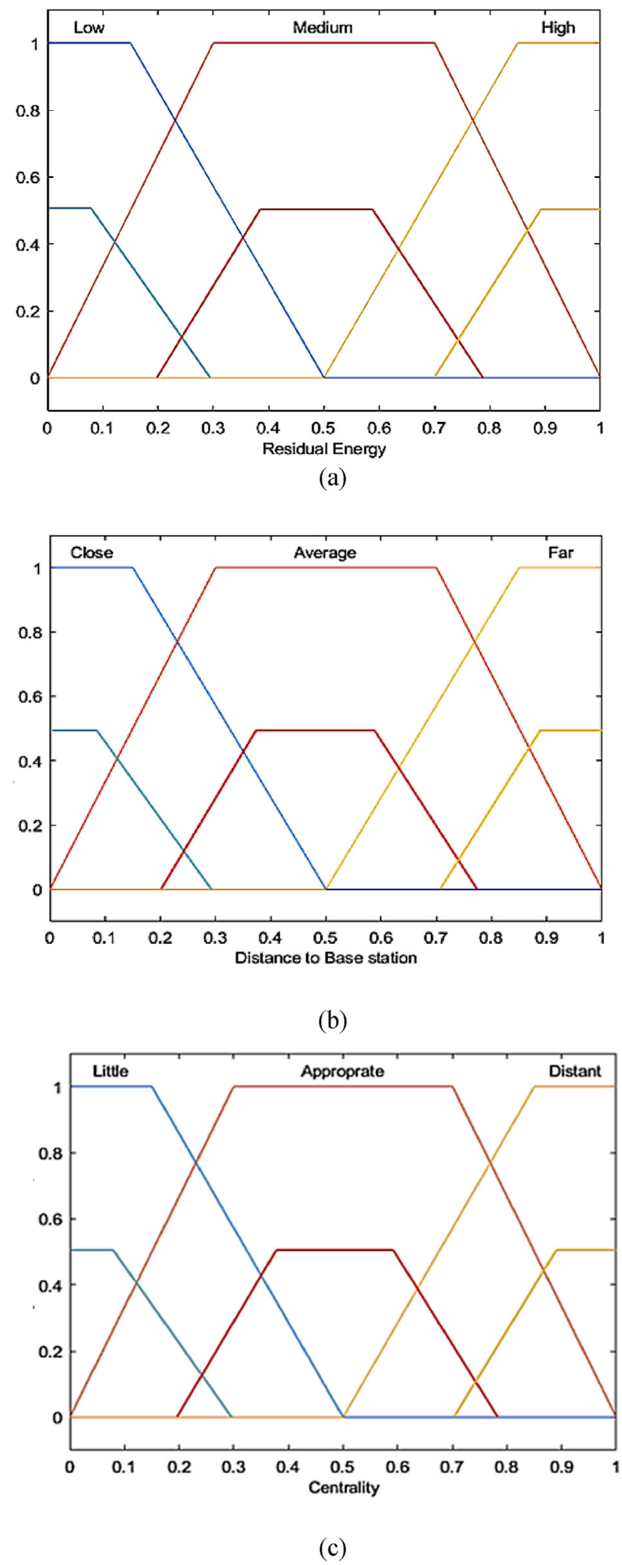

Fig. 2. FIS of the proposed protocol: (a) MFs of REN, (b) MFs of DBS, (c) MFs of CEN.

Table 2. Inputs/output linguistic variables.

Parameter	Linguistic variable
Residual Energy (REN)	Low (Low), Medium (Med), High (Hig)
Distance to BS (DBS)	Close (Cls), Average (Avg), Far (Far)
Centrality (CEN)	Little (Lit), Appropriate (App), Distant (Dst)
Chance	VL, LW, RL, LM, MD, HM, RH, HG, VH

Table 3. Output linguistic variables with intervals.

O/P MFs	Intervals
VL	0.0−0.1
LW	0.0−0.4
RL	0.2−0.4
LM	0.4−0.5
MD	0.4−0.7
HM	0.6−0.7
RH	0.7−0.8
HG	0.7−1.0
VH	0.9−1.0

display heterogeneity in their initial energy levels and are classified into three types: Normal Nodes, Advanced Nodes, and Super Nodes. The connections between nodes are considered to be symmetrical so that throughout packet transmission, the data rate and energy consumption between any two nodes stay identical.

In each iteration of the protocol, cluster heads are randomly chosen, incorporating the supplementary use of IT2-Fuzzy Logic criteria to enhance the Cluster Head (CH) selection process within the framework of the protocol. This integration aims to augment the efficacy and precision of CH selection during the protocol's execution.

5. Proposed protocol

The IT2F-HLEACH protocol follows the same approach as LEACH in terms of network formation. It divides the network into clusters with varying sizes, each containing a CH selected randomly based on additional IT2-Fuzzy Logic criteria. The nodes then send their sensed data to their corresponding CHs using single-hop communication, and the CHs aggregate the received data and transmit it to the BS.

To improve energy efficiency and the lifespan of the network, the Fuzzy Logic Controller employs three input parameters consideration: residual energy, node distance to the base station, and node centrality. Meanwhile, compared to other related protocols that use standard Type-1 Mamdani FLS for CH elections, which is a complex and inefficient method. The proposed protocol utilizes the TSK Interval Type 2 Fuzzy Inference System to handle network uncertainties more efficiently.

The suggested protocol works in rounds, which are organized into two phases: (I) The Set-Up Phase; and (II) The Steady-State Phase: During the Set-Up Phase, the BS sends an ADV message to all sensor nodes in the network, containing information about its location and power level. Each sensor node uses the information to calculate its distance from the BS, residual energy, and centrality, which are then used to generate IT2-FIS membership functions. The IT2-FIS output is employed to calculate each node's probability of becoming the CH for the current round. If a node's probability is less than the adjusted threshold and it meets the “chance” criterion, it is the CH for the present round.

In general, all sensor nodes vary in terms of initiating energy and are classified as (i) Normal Nodes, (ii) Advanced Nodes, and (iii) Super Nodes. Thus, the proposed approach has three degrees of energy heterogeneity: E_N, E_{Adv}, and E_{Sup}, representing the energy of Normal, Advanced, and Super nodes, respectively.

Table 4. Inputs/output rules.

NO.	REN	DBS	CEN	Chance	NO.	REN	DBS	CEN	Chance
1	Low	Cls	Lit	RL	15	Med	Avg	Dis	LM
2	Low	Cls	App	LW	16	Med	Far	Lit	HM
3	Low	Cls	Dst	VL	17	Med	Far	App	MD
4	Low	Avg	Lit	RL	18	Med	Far	Dst	LM
5	Low	Avg	App	LW	19	Hig	Cls	Lit	VH
6	Low	Avg	Dst	VL	20	Hig	Cls	App	HG
7	Low	Far	Lit	RL	21	Hig	Cls	Dst	RH
8	Low	Far	App	LW	22	Hig	Avg	Lit	VH
9	Low	Far	Dst	VL	23	Hig	Avg	App	HG
10	Med	Cls	Lit	HM	24	Hig	Avg	Dst	RH
11	Med	Cls	App	MD	25	Hig	Far	Lit	VH
12	Med	Cls	Dst	LM	26	Hig	Far	App	HG
13	Med	Avg	Lit	HM	27	Hig	Far	Dst	RH
14	Med	Avg	App	MD					

Assume that a greater proportion of the sensor nodes in the population are equipped with more energy resources than the normal nodes.

Let m = fraction of the overall number of nodes N.

Let n = a fraction of the total number of nodes m that are prepared with β times more energy rather than the normal nodes, mentioned as (Super Nodes). The remaining N*m*(1-n) nodes are prepared with α times more energy than the normal nodes; this is referred to as (Advanced Nodes), and the remaining N*(1-m) are regarded as Normal Nodes [33].

So that,

$$E_N = \text{Energy of the Normal nodes.} \tag{3}$$

The energy of the Advance and Super nodes is defined by:

$$E_{Adv} = (1+ \alpha) * E_N. \tag{4}$$

$$E_{Sup} = (1+ \beta) * E_N. \tag{5}$$

The total value of the initial energy of the network will be:

$$E_{initial} = N*(1-m) * E_N + N*m*(1-n) * (1+ \alpha) * E_N + N*m*n* (1+ \beta) * E_N. \tag{6}$$

In the heterogeneous scenario, the probability of each SN becoming a cluster head is expressed as follows:

I. For Normal Nodes

$$p_{Norm} = p \ / \ (1 + m*(\alpha+n*\beta)). \tag{7}$$

II. For Advance Nodes

$$p_{Adv} = (p*(1 + \alpha))/(1 + m*(\alpha+n*\beta). \tag{8}$$

II. For Super Nodes

$$p_{Sup} = (p*(1 + \beta))/(1 + m*(\alpha+n*\beta)). \tag{9}$$

Alternatively, it is possible to update the CH selection threshold equation for each sensor node by incorporating the following parameters:

I. For Normal Nodes

$$T_{hetro}\ (i) = p_{Norm}\ ((1/((1\text{-}p_{Norm}\ (r \bmod p_{Norm}))) + E_i\,/\,E_{max}) \tag{10}$$

II. For Advance Nodes

$$T_{hetro}\ (i) = p_{Adv}\ ((1/((1\text{-}p_{Adv}\ (r \bmod p_{Adv}))) + E_i\,/\,E_{max}) \tag{11}$$

III. For Super Nodes

$$T_{hetro}\ (i) = p_{Sup}\ ((1/((1\text{-}p_{Sup}\ (r \bmod p_{Sup}))) + E_i\,/\,E_{max}) \tag{12}$$

Where,

p_{Norm}, p_{Adv}, p_{Sup} = The probability of each node type (Normal, Advanced, and Super) to become a CH respectively, r = The present round's number, E_i = Remaining energy of the sensor node, E_{max} = maximum Energy of the sensor node.

The revised formula for CH selection aims to increase the likelihood of the node with the highest remaining energy being selected as a CH. Once the CHs have been chosen, they send ADV messages to their respective SNs to join their clusters. Each SN chooses which CH it wants to participate in based on the overall strength of the received signal (RSSI).

During the Steady-State Phase, each CH generates a TDMA schedule depending on the variety of cluster members (CMs), and each sensor node transmits data packets within its time slot. The CH collects data from its CMs and sends it to the BS. The method is performed in successive rounds until the network's lifetime is achieved.

A detailed illustration of the Set-Up Phase of the IT2F-HLEACH Protocol can be found in Fig. 3, Correspondingly, the general steps of the IT2F-HLEACH protocol are illustrated in Algorithm 1.

Algorithm 1. The Proposed IT2F-HLEACH

1: **Begin:**
2: The BS broadcasts a request for ID, residual energy, distance to BS, and centrality for the SNs in the network and waits for responses.
3: **Run the proposed fuzzy system**
4: Define REN, DBS, and CEN as inputs to IT2-FIS.
5: Execute IT2-FIS based on the rule-based.
6: Acquire the chance values
7: Select CH based on the following criteria:
IF (rand (0,1) < T_{hetro} (i) & chance $\geq$ Q) then the node is selected as a CH.
Otherwise, the node is selected as a CM.
8: For each CH
9: Broadcast advertisement (ADV) messages to all SNs to join it.
10: Based on the received signal strength (RSSI), the SNs join its CH.
11: Create a TDMA schedule according to the number of CMs.
12: CH collects the data from its CMs and transmits it to the BS.
13: End For
14: **End**

Q = Fuzzy threshold value = 0.2.

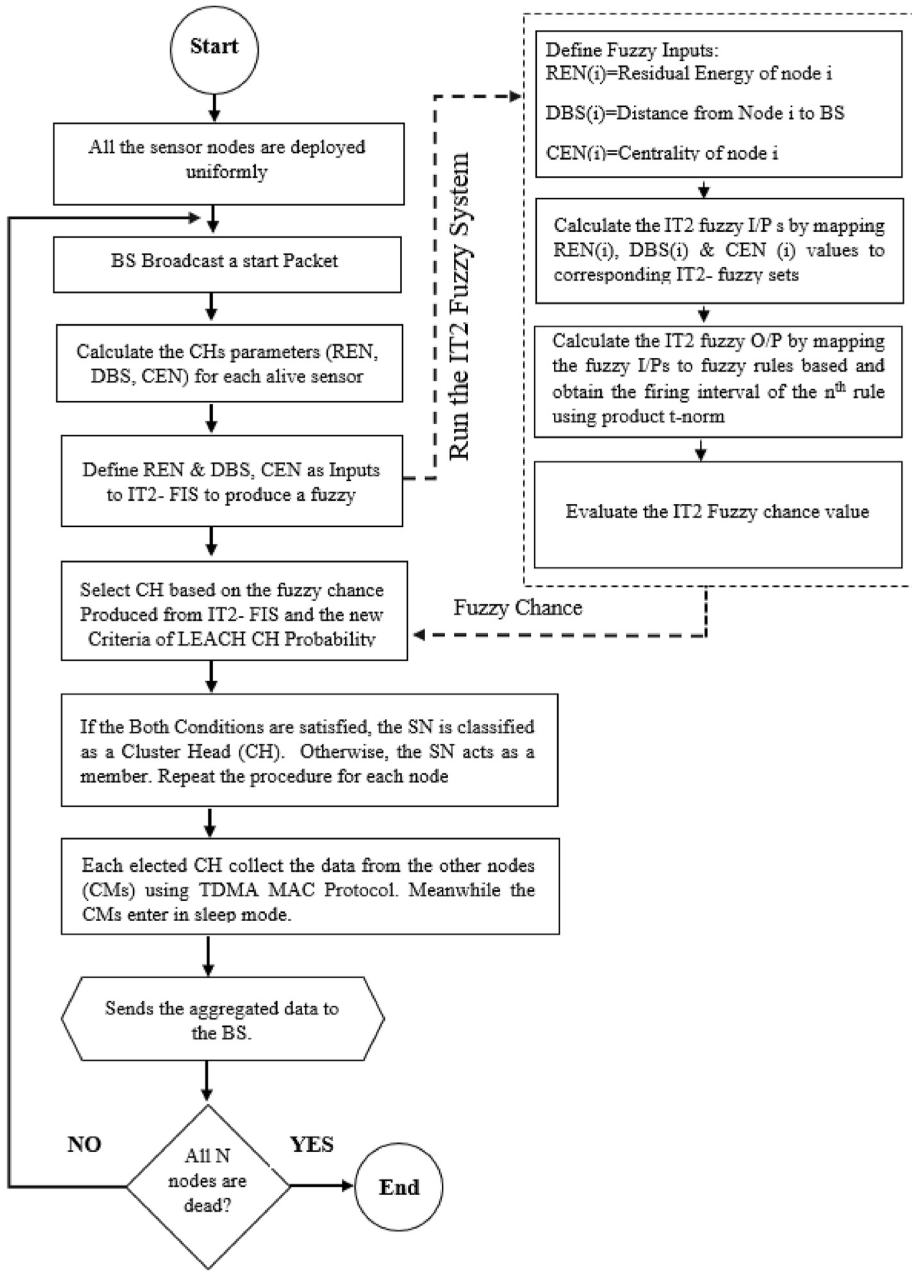

Fig. 3. Set-up phase of EEIT2-FLEACH protocol using proposed IT2 fuzzy-based algorithm.

6. Simulation and results

6.1. System parameters and performance metrics

In this section, we evaluate the performance of the proposed protocol using the OMNeT++ Simulator and Castalia framework. Our experiments aim to assess the effectiveness of the protocol in various network scenarios, including different network topologies, node distributions, and communication radio types.

The experiments were performed on a network simulation environment consisting of 100 Sensor Nodes (SNs) distributed uniformly over an area of 100 $\times$ 100 m, with the Base Station (BS) located at the center of the sensor field. Each SN had an initial energy of 1 J and 3 J. The number of nodes and clusters were established at 100 and 5, respectively. Additionally, the communication packet size was set to 2000 bytes with a bandwidth of 1Mbps.

To evaluate the performance of the proposed protocol, we conducted a series of experiments that tested the protocol's ability to prolong the lifespan of the network, decrease energy usage, and successfully transmit a packet over a series of rounds. The

Table 5. Simulation parameters.

Type	Parameters	Value
Network topology	Network size	$100 \times 100m^2$
	No. of nodes	100
	No. of clusters	5
	Location of BS	50×50 m
Radio model	Energy model	Battery
	Initial energy	1 Joule, 3 Joule
	Communication radio type	CC2420
Application	Simulation time	300 S
	Round time	20 Sec
	Data packet size	2000 bytes
	Bandwidth	1Mbps
	Application ID	Throughput test

settings of these experiments are presented in Table 5, which outlines the simulation parameters.

The proposed protocol has been implemented and compared to the SEP, and EEHC protocols based on the following performance metrics: Average remaining energy at each nod, First Node Dead (FND) or (Stability Period) which represents the time until the first node dead, Last Node Dead (LND), Throughput, and Latency which is the time expected for a packet to be transmitted from the source to the BS, which is defined as a histogram in Castalia.

6.2. Performance evaluation of the proposed protocol

In this study, we evaluated the performance of the IT2F-HLEACH protocol for energy-efficient communication in WSNs through extensive simulations. Specifically, we assumed to be heterogeneous.

This study aims to evaluate the performance of the IT2F-HLEACH protocol in two distinct heterogeneous network scenarios: A Two-Level Heterogeneous Scenario and a Three-Level Heterogeneous Scenario.

For Two-Level heterogeneous configurations, 80 % of nodes are considered Normal Nodes with initial Energy equal to E_0. Meanwhile, the remaining 20 % of nodes act as Advanced Nodes and have initial energy equal to $(1 + \alpha)$ times that of Normal Nodes (i.e. initial energy of each Advance node $= (1 + \alpha) E_0$.)

In the Three-Level Heterogeneous Scenario, 50 % of nodes are distributed as Normal Nodes and each has an initial energy equal to E_0. Meanwhile, 30 % act as Advanced Nodes with initial Energy for each node equal to $(1 + \alpha) E_0$, Finally, 20 % of nodes have starting energy $(1 + \beta) E_0$ for each one and act as Super Nodes.

The simulations are used to evaluate the proposed protocol performance in heterogeneous configuration with different node initial energy $E_0 = 1$ J, and 3 J, respectively. According with $\alpha = 2$; and $\beta = 5$. The results of the proposed protocol are compared according to the total remaining energy, FND, LND, Throughput, and latency (ms).

The findings indicate that the proposed protocol outperforms the SEP and EEHC protocols in terms of energy savings in both heterogeneous scenarios with an initial energy of 1 J. Specifically, Fig. 4 shows that the proposed protocol achieves a higher energy savings ratio compared to the other two protocols in both scenarios. Accordingly, the results show that the proposed protocol saves 54.08 %, and 69.65 % of the total energy in the two suggested heterogeneous scenarios; While SEP and EEHC protocols save only 25.49 %, and 40.10 % respectively for the total remaining energy in each node at the first 80s, at the 200s, EEHC protocol saves only 10.33 %, while the IT2F-HLEACH saves 22.093 % of the total remaining.

Furthermore, the results of the Three-Level Heterogeneous Scenario demonstrate that the proposed protocol progresses the network's lifetime and stability period by 127.68 % and 15.38 %, respectively, as shown in Fig. 5 Additionally, Fig. 6 illustrates that the throughput of IT2F-HLEACH is superior to that of SEP and EEHC protocols in both the Two-Level and Three-Level Heterogeneous Scenarios.

Fig. 7 showed that IT2F-HLEACH in Two-Level Heterogeneous had 350.67 % more remaining energy than SEP with 3 J initial energy, and in Three-Level Heterogeneous it was 78.71 % better than EEHC at 200s. Fig. 8 indicates that in Three-Level Heterogeneous, the proposed protocol increases the network lifetime (LND) by 91.056 % and the stability by around 1.29 %. Furthermore, Fig. 9 shows the throughput of IT2F-HLEACH for Two-Level and

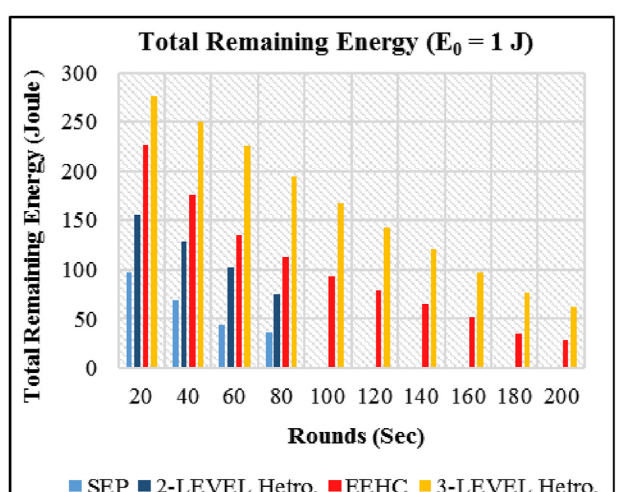

Fig. 4. Total remaining energy (Initial energy = 1 J).

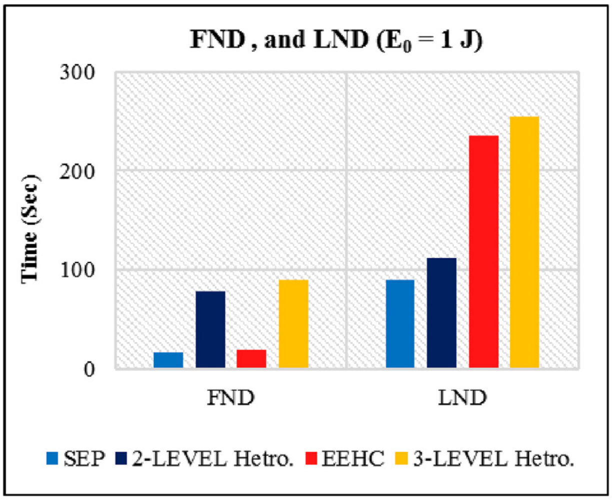

Fig. 5. FND, and LND (Initial energy = 1 J).

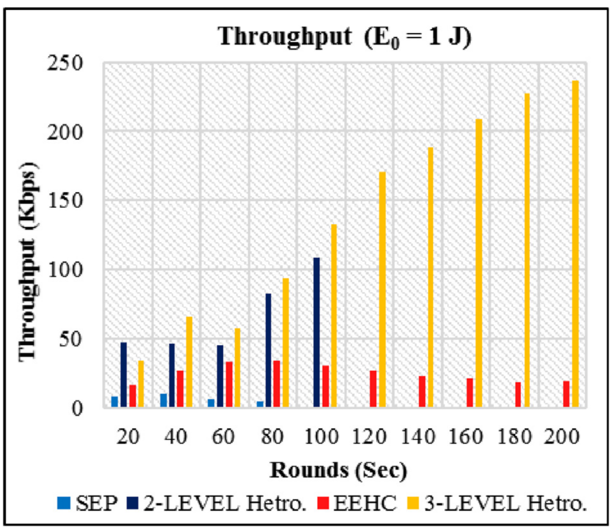

Fig. 6. Throughput Vs rounds (Initial energy = 1 J).

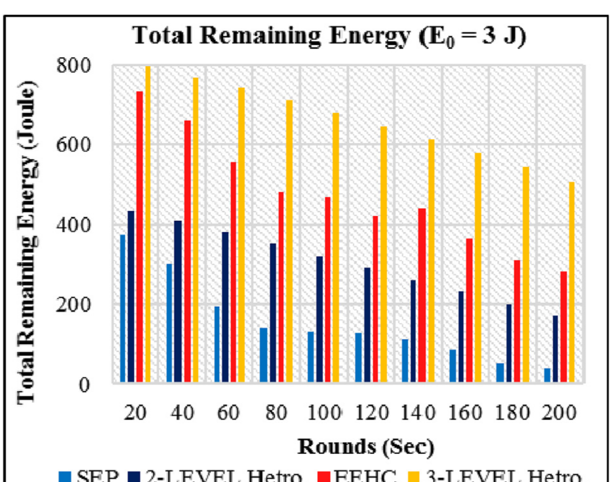

Fig. 7. Total remaining energy (Initial energy = 3 J).

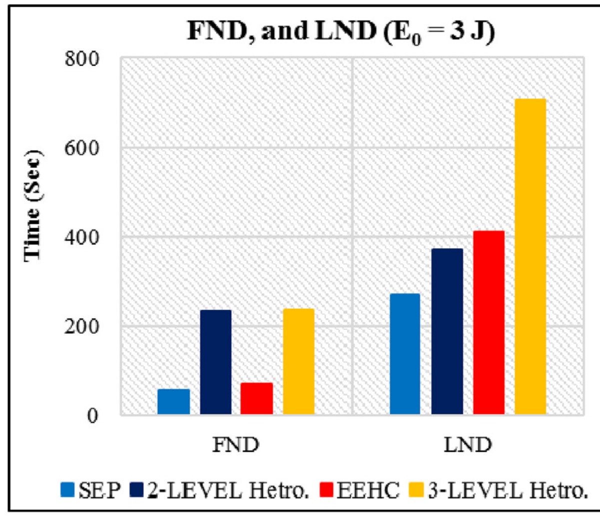

Fig. 8. FND, and LND (Initial energy = 3 J).

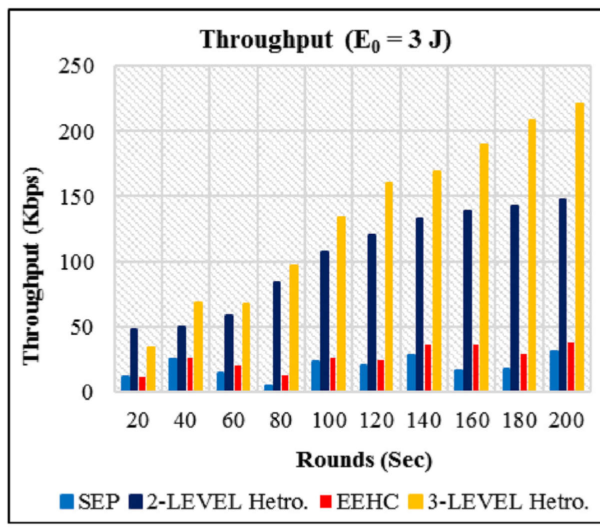

Fig. 9. Throughput Vs rounds (Initial energy = 3 J).

Three-Level Heterogeneous scenarios was significantly improved as compared to both SEP and EEHC protocols. This finding may be explained by the fact that the lifespan of the IT2F-HLEACH protocol is significantly longer in the Three-Level Scenarios and Two-Level Heterogeneous scenario than in SEP and EEHC, resulting in an imperative increase in the amount of data transmitted to the sink node.

In conclusion, the study demonstrates that the IT2F -HLEACH protocol outperforms existing protocols in terms of energy savings and network performance in both heterogeneous scenarios.

The results of this study highlight the potential of the proposed protocol for improving the efficiency and reliability of WSNs in diverse scenarios. Table 6

Table 6. Latency Percentage Vs Rounds with $E_0 = 1$ Joule.

Rounds	[0−20]	[20−40]	[40−60]	[60−80]	[80−100]	[100−120]	[120−140]	[140−160]	[160−180]	[180−200]	[200-inf]
Two-level heterogeneous IT2F-HLEACH protocol											
20	100 %	0	0	0	0	0	0	0	0	0	0
60	87.86 %	0	0	3.130 %	0	0	2.935 %	0	0	1.174 %	4.8921
100	94.91 %	0.048 %	0	1.369 %	0	0	1.223 %	0	0	0.489 %	1.956 %
Three-level heterogeneous IT2F-HLEACH protocol											
20	100 %	0	0	0	0	0	0	0	0	0	0
60	88.525 %	0	0	2.170 %	0	0	3.1 %	0	0	1.705 %	4.496 %
100	94.43 %	0	0	1.45 %	0	0	1.209 %	0	0	0.806 %	2.0958 %
140	96.527 %	0.141 %	0	1.070 %	0.020 %	0	0.686 %	0	0	0.444 %	1.1104 %
180	97.160 %	0.104 %	0	1.185 %	0.013 %	0	0.5079 %	0	0	0.286 %	0.742 %

Table 7. Latency percentage Vs rounds with $E_0 = 3$ Joule.

Rounds	[0−20]	[20−40]	[40−60]	[60−80]	[80−100]	[100−120]	[120−140]	[140−160]	[160−180]	[180−200]	[200-inf]
Two-level heterogeneous IT2F-HLEACH protocol											
20	100 %	0	0	0	0	0	0	0	0	0	0
60	88.41 %	0	0	2.757 %	0	0	2.573 %	0	0	1.284 %	4.96 %
100	94.745 %	0	0	0.049 %	0	0	1.090 %	0	0	0.594 %	2.330 %
140	96.763 %	0.0286 %	0	0.7448 %	0	0	0.716 %	0	0	0.401 %	1.346 %
180	97.650 %	0.0207 %	0	0.540 %	0	0	0.519 %	0	0	0.291 %	0.977%
Three-level heterogeneous IT2F-HLEACH protocol											
20	100 %	0	0	0	0	0	0	0	0	0	0
60	88.49 %	0	0	2.177 %	0	0	2.954 %	0	0	2.022 %	4.35 %
100	94.31 %	0	0	2.227 %	0.039 %	0	1.1535 %	0	0	0.9149 %	2.06 %
140	96.088 %	0.0449%	0	1.1915 %	0.022 %	0	0.786 %	0	0	0.607 %	1.259 %
180	96.77 %	0.0284 %	0	1.236 %	0.014 %	0	0.7104 %	0.014 %	0	0.397 %	0.824 %

The elevated percentage of packet latency observed between 0 to 20 seconds indicates that the sink received the sensed information promptly as required by a WSN.

and Table 7 display the packet latency for energy levels of 1 J and 3 J, respectively. The higher rate of packet latency experienced within the first 20 s suggests that the sink received the sensed data promptly, meeting the WSN's timing requirements.

7. Conclusion

This paper presents a new cluster-based routing approach that incorporates the IT2-TSK Fuzzy Logical principle to address the energy consumption in WSNs. The proposed protocol aims to progress the network lifetime and reduce energy consumption through the intelligent management of sensor nodes. To this end, this study uses IT2- Fuzzy Logical systems to estimate CH probability. Additionally, a proposed method investigated the heterogeneous scenarios with many initial energies from various perspectives. The simulation results, obtained using the OMNeT++ simulator and the Castalia framework, revealed remarkable improvements across key network metrics. Specifically, the reduction of power usage, improvement of network lifespan due to the delay of FND and LND occurrences, improving data transmission speeds, and reduction of latency. These results highlight the efficiency of our suggested procedure in improving overall network performance as compared to SEP and EEHC protocols. Furthermore, the performance of the suggested protocol was concluded based on two heterogeneous Scenarios: Two-Level Heterogeneous scenario, and Three-Level Heterogeneous scenario. The results indicate that the protocol in the Three-Level scenario approach outperforms the Two-Level scenario by multiple times. Additionally, the suggested protocol is intended to be adaptable to different network sizes by changing clustering decisions according to network conditions and node capabilities.

Although new advancements have been achieved in this work, it is important to acknowledge the restrictions and difficulties in implementing the suggested protocol in practical WSNs. Computational complexity continues to be a typical issue due to the use of IT2-Fuzzy Logic. In addition to the sensor nodes' limited resources, which include short battery life and low computational capacity, external factors such as temperature changes and network topologies may have a negative impact on sensor performance and reliability. To address these concerns, different intelligent algorithms are suggested to be implemented to fixed environmental conditions, guaranteeing reliable performance in different situations. Furthermore, diligent consideration of deployment strategies and maintenance protocols will be essential for the successful practical implementation of our discoveries.

In future work, we intend to incorporate intelligent algorithms that include clustering aggregations. Furthermore, we will analyze how mobile node movements affect network coverage, taking into account random and pre-determined mobility patterns.

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The work does not involve any data that requires ethical approvals.

Conflicts of interest

The authors declare that they have no competing interests.

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