# Application of Enhanced Hierachical Algorithm for Base Station Energy Management in LTE Access Network of 4G Broadband System

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## ABSTRACT

One of the major challenges in base station 4G broadband communication system is efficient energy management. An enhanced hierarchical algorithm can be used to improve this energy management issues. Fuzzy logic algorithm for optimum target-based station was developed, a hierarchical routing algorithm for improving energy saving of Long-Term Evolution (LTE) access network was equally developed. Then, energy savings resulting from the hybrid application developed algorithm was evaluated and a SIMULINK model for the simulation and analysis of the LTE access network energy saving was designed and validated. The results obtained were Mean residual energy for Non-hierarchical technique which was 8.2300J. In non-hierarchical algorithm, there is no cluster head formation. (The non-hierarchical technique allows all eNodeB transmission to go directly to the BS) Mean residual energy for 2 Cluster Head (CH) hierarchical routing when fuzzy controller was imbibed in the system was 11.1541J. With these results obtained, it definitely meant that percentage enhancement in the energy efficient model for base station management in 4G broadband system when fuzzy based hierarchical algorithm was integrated into the system was 36.6%. Furthermore, the hierarchical clustering approach extended the network lifetime by approximately 52.5% for three-cluster head hierarchical routing model compared to the conventional non-hierarchical system. The study proposed an energy-efficient LTE base station management model using three cluster formations with hierarchical routing. Cluster head election was based on transmission energy estimates, with role rotation and data aggregation to optimize performance. MATLAB simulations showed improved eNodeB energy efficiency, while further research is recommended on four or five cluster formations for greater efficiency. The study develops a hierarchical–fuzzy logic framework for 4G base stations, enabling dynamic energy-efficient management through adaptive algorithms. Simulations show reduced energy waste, improved decision-making, and support for green ICT**,** providing a foundation for future 5G/6G research.

**Keywords**: Energy, efficient model, base station management, 4G broadband system, enhance hierarchical algorithm.

## INTRODUCTION

The rapid growth in mobile communication technologies, especially the evolution from 3G to 4G networks, has led to a significant rise in the number of base stations to meet the high demand for data traffic and seamless connectivity. However, this expansion has caused a substantial increase in energy consumption, making base station operation one of the most energy-intensive components in cellular networks Hasan et al. (2011). In response to this, energy efficiency in wireless communication systems has become a critical area of research and development. In mobile networks, base stations are responsible for approximately 60–80% of total energy consumption, making them the primary contributors to operational expenditure (OPEX) (Mishra et al., 2019; Zhang & Wang, 2019). In many emerging economies, where grid power is unreliable, network operators depend heavily on diesel generators and backup power systems, further increasing operational costs and negatively impacting network reliability (Zeller et al., 2013; Hossain et al., 2018).

In 4G broadband systems, base stations typically account for more than 60% of the total energy consumption in mobile networks Oh & Krishnamachari. (2013). This has sparked interest in developing intelligent energy-

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efficient models that can optimize energy usage while maintaining the quality of service (QoS). Traditional energy-saving methods, such as sleep mode strategies and load-adaptive control, have shown limitations in terms of scalability, responsiveness, and overall efficiency under dynamic network conditions Marsan et al. (2009). Recent advancements have introduced intelligent algorithms, particularly hierarchical control techniques, as a means to address the inefficiencies in base station energy management. Hierarchical algorithms enable structured decision-making processes by dividing the control architecture into multiple layers, each responsible for specific energy-related functions. When combined with enhanced optimization strategies, such as fuzzy logic or machine learning, these models provide more flexible and adaptive solutions to reduce energy waste without degrading service quality. Zhang et al. (2016). The development of an enhanced hierarchical algorithm aims to intelligently manage resources at various control layers of the base station by adapting to real-time traffic loads, user mobility, and environmental factors. Such an approach not only improves energy efficiency but also extends the lifespan of hardware components and reduces operational costs Auer et al. (2011). Therefore, the implementation of energy-efficient models using enhanced hierarchical algorithms is vital for sustainable 4G network operations and serves as a foundation for the transition to next-generation networks.

Review of Base Station Management Strategies: This paper reviews existing research on energy-efficient management of cellular networks, focusing on base station switching strategies. Studies have explored various approaches, including:

Distributed base station switching: Li et al. (2011) achieved significant energy savings by switching off underutilized base stations based on traffic profiles.

Cell zooming: Niu et al. (2010) dynamically adjusted cell sizes based on user needs and traffic load, optimizing energy usage.

Dynamic base station shutdown: Oh et al. (2018) proposed a system based on daily traffic patterns, achieving nearly 35% energy savings.

Profile-based approaches: Kim et al. (2013) and Zhao et al. (2015) reduced power consumption in 3G networks by turning off underutilized base stations.

Cooperative strategies: Han et al. (2013) achieved over 50% energy savings during low traffic periods using cooperative base station switching.

However, these studies have limitations, such as overlooking dynamic variations in neighbouring base stations, heterogeneous traffic patterns, and non-uniform user distribution. Future research should focus on addressing these challenges to improve energy efficiency in cellular networks.

Table 1: Key findings with limitation:

| Study | Approach | Energy saving | Limitations |
|---|---|---|---|
| \| Li et al. (2011) | Distributed switching | Significant | Overlooked dynamic variations |
| \| Niu et al. (2010) | Cell zooming | Optimized energy usage | Limited consideration of traffic load |
| \| Oh et al. (2018) | Dynamic shutdown | 35% | Fixed power consumption model |
| \| Kim et al. (2013) | Profile-based | Significant | Cooperation issues |
| \| Han et al. (2013) | Cooperative switching | 50% | Overlooked traffic distribution |

# METHODOLOGY

**Mathematical model of the proposed hierarchical routing technique for energy saving:**

The model for the hierarchical routing protocol energy saving algorithm involves cluster formation, data aggregation, data transmission, energy management and routing optimization. In this model, the energy

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consumption of a node *i* is denoted as $E_i$, while the energy threshold for the selection of cluster head is denoted as $E_{threshold}$, then, the consumed energy for communication is denoted as $E_{comm}$.

For the selection of cluster head, if $E_i > E_{threshold}$, node *i* will become the cluster head (CH). Hence,

The first stage CH selection is the initial energy measurement stage, which checks the initial energy of the node *i* depicted as $E_{in(i)}$, then the next stage is the measurement of distance from the node depicted as d(*i*). The next stage involves the estimation of energy for transmission within the cluster for two and three formations of clusters within a cluster area, this is represented in equation (1)

$$E_{trans}(i) = E_{amp} \times k \times d(i)^2 \quad (1)$$

Where:

$E_{trans}$ = energy transmission,

$E_{amp}$ = energy required for amplification and k is proportionality constant.

The next stage presented in equation (2) and (3) are for maximum energy estimation and CH selection as follows:

$$MaxEnergy(i) = Ein(i) - E_{trans}(i) \quad (2)$$

$$CH(i) = argmax_i(MaxEnergy(i)) \quad (3)$$

$$E_{total} = Distance \times E_{comm} \quad (4)$$

Equation (4) presents the model for calculating the total energy consumption for communication transmission. While the metric for energy saving is presented in equation (5) as follows:

$$Energy\ Saving\ Ratio = \frac{Energy\ Consumption\ without\ HR - Energy\ Consumption\ with\ HR}{Energy\ Consumption\ without\ HR} \times 100\% \quad (5)$$

Where HR stands for Hierarchical Routing.

In the study, the hierarchical routing protocol for energy saving considers when there are 2 or 3 cluster heads present in the network location for optimal routing process, the model that considers the cluster heads involves:

The calculation of cluster head selection probability using equation (6) as follows:

$$\text{Cluster head probability} = P_{CH}(i)\frac{E_i}{\sum_{j=1}^{N} E_j} \quad (6)$$

Where $P_{CH}(i)$ is the probability of cluster head selection for node *i*. Then, the system implements data aggregation, inter-cluster communication, energy management and optimum target base station selection models from equations (1) to equation (6) for the determination of optimal hierarchical routing protocol for efficient energy saving.

After determining the optimal routing protocol that ensure proper energy saving, the next phase is the selection of the optimum base station in order to maintain the efficiency of the communication network and energy consumption level. The selection of base station from a number of available base stations requires the consideration of various factors like distance (proximity), traffic load, quality of service (QOS), number of users and signal strength of the network. Therefore, this study adopts fuzzy logic algorithm for the selection of the target base station.

**Development of a fuzzy logic algorithm for optimum target base station selection**

This presents a particular application scenario based on multiple attribute decision-making in Long Term

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Evolution (LTE) access networks, target categorization difficulties. It is suggested to use intuitionistic fuzzy sets (IFS) as the foundation for a decision fusion model with many characteristics. Additionally, to validate the suggested IFS model methodology. First, a number of presumptions are made in order to make the research easier:

- Sensor nodes are evenly and randomly distributed over a level surface without any obstructions (line of sight),
- Every node uses its GPS module to determine its location, which it then transmits to the fusion centre for decision aggregation,
- The suggested multiple attributes decision fusion technique is utilised to obtain the classification result after the target's many characteristics are monitored by each sensor node, which is composed of various modules.

Figure 1 displays the IFS model in an LTE access network. Numerous sensors are keeping an eye on the target.

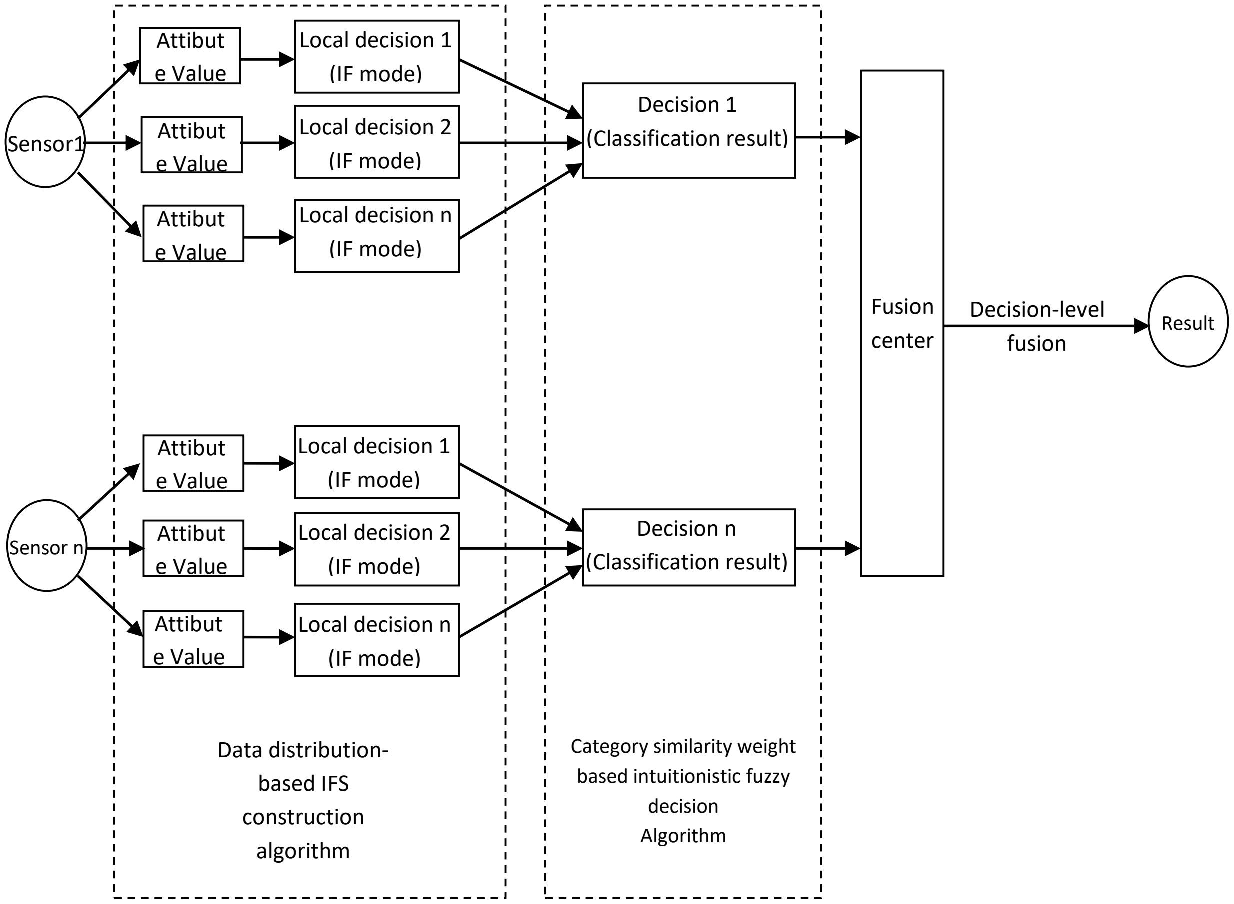


Figure 1: The Multiple attribute decision making -IFS model in LTE access network

The suggested technique states that each eNodeBs converts each attribute value into a set of IF values which represent the target membership degree for each attributes potential categories after the data collecting procedure. Each node combines the IF values into a single classification decision based on the intuitionistic fuzzy decision algorithm technique for order preference by similarity to ideal solution, which is weighted based on category similarity. The combined judgements are then forwarded to Fuzzy Construction (FC). By using fusion rules, the FC combines the local judgements it has received to arrive at a final outcome.

**Fuzzy Sets and Linguistic Variables:**

The fuzzy sets $A_1$, $A_2$, and $A_3$ define the linguistic classifications of the input parameters used in the fuzzy logic decision-making process.

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Following the information tables 2 and 3, each eNodeB selects its neighbour's average residual energy (NNE), neighbour degree (ND), and residual energy (NE) as input parameters. It then transforms these values into fuzzy linguistic variables to carry out the fuzzy logic analysis and determine the eNodeBs' performance evaluation. The sets $A_1$, $A_2$, and $A_3$ represent the fuzzy sets for the input parameters used in the performance evaluation of eNodeBs, the $X_1$, $X_2$ and $X_3$ represents the energy classification. These sets are defined as follows:

**Fuzzy Set for Residual Energy (NE):**

$$A_1 (NE) = \{X_1 = \text{“low”}, X_2 = \text{“medium”}, X_3 = \text{“high”}\} \quad (7a)$$

Where:

$X_1$ = Low residual energy

$X_2$ = Medium residual energy

$X_3$ = High residual energy

**Fuzzy Set for Neighbour Degree (ND):**

$$A_2 (ND) = \{X_1 = \text{“short”}, X_2 = \text{“average”} , X_3 = \text{“long”} \} \quad (7b)$$

Where:

$X_1$ = Low residual energy

$X_2$ = Average residual energy

$X_3$ = High residual energy

**Fuzzy Set for Neighbour's Average Residual Energy (NNE):**

$$A_3 (NNE) = \{X_1 = \text{“weak”}, X_2 = \text{“normal”}, X_3 = \text{“strong”}\} \quad (7c)$$

Where:

$X_1$ = Weak Average residual energy

$X_2$ = Normal Average residual energy

$X_3$ =Strong Average residual energy

As can be seen, the membership degree divisions for the fuzzy linguistic variable for eNodeBs residual energy are "low," "medium," and "high," for the fuzzy linguistic variable for eNodeBs degree, they are "low," "average," and "high," and for the fuzzy linguistic variable for neighbour nodes' average residual energy, they are "weak," "normal," and "strong."

Equation (7) contains the segmented membership function for each of the input fuzzy linguistic variables. The original crisp values will be appropriately converted to fuzzy linguistic variables by the fuzzy inference system. The IF-THEN rules that follow the Takagi-Sugeno-Kang (TSK) deductive system's methodology are in the form of: IF (antecedent) THEN (consequence)

where:

a) Antecedent: a set of conditions or inputs that trigger the rule
b) Consequence: A set of outputs or actions that result from the rule

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Table 2 displays the algorithm's IF-THEN rules table. The symbols for the residual energy are NE, the eNodeBs distance is ND, and the average residual energy of the neighbouring eNodeBs is NNE.

The Energy Classification (NE – eNodeBs Energy) is as follows:

(0.1 – 0.4) = Low (1)

(>= 0.4 < 0.7) = Medium (2)

(>= 0.7) = High (3)

Table 2: IF-THEN rules

| SN | NE | CH | ND | NNE | Result | eNodeBs |
|---|---|---|---|---|---|---|
| 1 | Low | Low | short | weak | Check other cluster heads | All nodes |
| 2 | Medium | High | short | weak | Transmit | 1 |
| 3 | High | High | short | weak | Transmit | 1 |
| 4 | Low | Low | Long | strong | Transmit | 2 |
| 5 | Low | Medium | Long | strong | Transmit | 2 |
| 6 | Medium | medium | Long | normal | Transmit | 1 |
| 7 | Medium | medium | Long | strong | Transmit | 2 |

Based on the aforementioned input membership functions, the fuzzy inference system (FIS) transforms the original crisp input variables into matching fuzzy linguistic variables. Making the instantiation of linguistic expressions, like the well-known IF premise, THEN conclusion, is the most common method in the field of fuzzy logic to model human thought processes. Here, the premise is the decision condition described by the fuzzy linguistic variables in the fuzzy set of input parameters, and the conclusion is regarded as the fuzzy output variable. Natural language models and representations serve as the foundation for the IF-THEN rule-based knowledge representation. This indicates that the rules that encapsulate the evaluation system experts' knowledge are used by the fuzzy engine to determine the value of the output variables.

**The Mathematical model for target base station selection using fuzzy logic algorithm:**

Fuzzy logic provides an effective approach for optimizing target base station selection in LTE wireless communication systems. The proposed fuzzy logic model considers multiple network parameters to improve communication efficiency, reduce energy consumption, and maintain Quality of Service (QoS).

**The Mathematical model is presented as follows:**

a) **Input Variables:**

The input variables considered in the fuzzy inference system include:

i. Received Signal Strength Indicator (RSSI)

ii. Distance

iii. Number of Users ($NumUsers$)

iv. Traffic Load

v. Quality of Service Requirements (QoS)

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Table 3: Input Parameters

| Symbol | Name | Interpretation |
|---|---|---|
| **NE** | Neighbour Residual Energy | Remaining energy available in a neighbouring eNodeB |
| **ND** | Neighbour Degree | Number of neighbouring eNodeBs connected to a particular eNodeB |
| **NNE** | Neighbour's Average Residual Energy | Average residual energy of surrounding neighbouring eNodeBs |

Membership function of the fuzzy sets are defined as:

Table 4: Membership function.

| Parameters | Linguistic Variables |
|---|---|
| RSSI | Low, Medium, High |
| Distance | Near, Medium, Far |
| Number of Users (NumUsers) | Low, Medium, High |
| Traffic Load | Low, Medium, High |

From tables 3 and 4, the fuzzy rules and decision-making were formulated as shown below:

The fuzzy decision rules are formulated based on network conditions. For example:

i. If RSSI is high, distance is near, and the number of users is low, then the base station is selected as the preferred target base station.

ii. If traffic load is high or QoS requirements are not satisfied, the candidate base station is avoided.

The membership functions of the fuzzy inference system are represented as:

$$\mu_{RSSI}(a), \mu_{Distance}(b), \mu_{NumUsers}(c), \mu_{TrafficLoad}(d)$$

The aggregated fuzzy output for the $i^{th}$base station is expressed as:

$$Output(i) = \mu_{RSSI}(a) \times \mu_{Distance}(b) \times \mu_{NumUsers}(c) \times \mu_{TrafficLoad}(d) \qquad (8)$$

Where:

$Output(i)$represents the suitability score of the $i^{th}$candidate base station.

**Adjacent eNodeBs**

To support traffic transfer and coverage expansion, each eNodeB maintains information about neighbouring eNodeBs within the LTE access network. Two eNodeBs are considered neighbours when the distance between them is less than or equal to $\sqrt{3}$□, where □ represents the radius of a hexagonal cell. The neighbouring eNodeBs are stored in a neighbouring matrix denoted as □□□□. The matrix consists of □rows and 6 columns, since a hexagonal cell can have a maximum of six neighbouring cells. The neighbouring matrix is represented as:

$$N_{MAT} = [n_{i,1}\ n_{i+1,1}\ \cdots\ n_{6,1}\ \cdots\ n_{i,N}\ n_{i+1,N}\ \cdots\ n_{6,N}] \qquad (9)$$

Where:

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a. $N$represents the total number of eNodeBs in the LTE network,
b. $n_{i,N}$ to $n_{6,N}$ represent neighbouring eNodeBs associated with the $N^{th}$eNodeB.

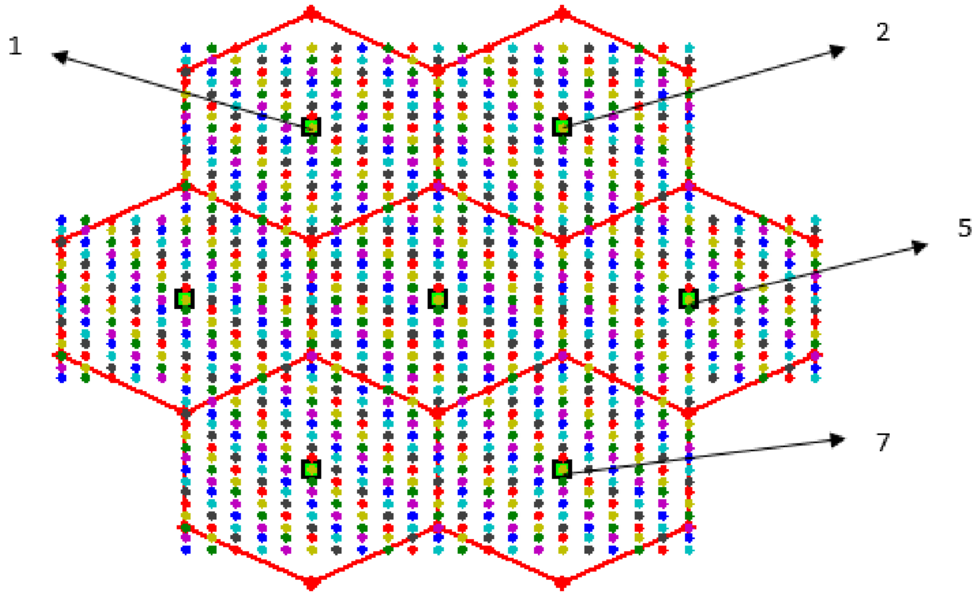


Figure 2: The relationship between uniform distribution of mobile stations, eNodeBs, and cells

The MATLAB code for generating $N_{MAT}$ is given in Appendix A whose pseudo code is:

Pseudo code: eNodeB neighbors

*Start*
*For each cell from the first cell to the last cell do*
*Compute the distance between neighbouring base stations*
*If Distance ≤ √3R then*
*The cells are classified as neighbouring eNodeBs*
*Else*
*The cells are not neighbouring eNodeBs*
*End If*
*End For*
*Stop*

For the cellular network shown in figure 2, the $N_{MAT}$ is given as

$$N_{MAT} = [234000\ 145000\ 146000\ 123567\ 247000\ 347000\ 456000] \tag{10}$$

Equation (10) shows that eNodeB 2, 3, and 4 are the surrounding eNodeBs of eNodeB 1 in figure 2. eNodeBs 1, 4, and 5 are eNodeBs that are next to eNodeB 2. eNodeB 3's surrounding eNodeBs are eNodeBs 1, 4, and 6. eNodeBs 1, 2, 3, 5, 6, and 7 are the eNodeBs that surround eNodeB 4. The surrounding eNodeB 5 are eNodeBs 2, 4, and 7. eNodeBs 3, 4, and 7 are the eNodeBs that surround eNodeB 6. The surrounding eNodeB 7 are eNodeBs 4, 5, and 6. Under the dynamic mobile station sharing/transfer scenario, an eNodeB can only share or transfer its mobile station to other eNodeBs.

**Defuzzification**

Defuzzification converts fuzzy output values into a single crisp value for decision-making within the fuzzy logic system. In this study, the centroid method is adopted to determine the optimal target base station.

The centroid defuzzification model is expressed as:

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$$Optimum\ Base\ Station = \frac{\sum_i [Output(i) \times i]}{\sum_i Output(i)} \quad (11)$$

Where:

i. The output represents the aggregated fuzzy output of the $i^{th}$candidate base station,

ii. $i$ denotes the positional index of the candidate base station.

The numerator represents the weighted summation of the fuzzy outputs and their corresponding indices, while the denominator represents the total aggregated fuzzy membership values. The resulting ratio produces a crisp output corresponding to the optimal base station.

For the selection of the optimum base station among multiple cluster heads, the fuzzy decision model is further defined as:

$$Optimum\ Base\ Station = \arg\max_i [\mu(E_{trans}(i)) \times \mu(d(i))] \quad (12)$$

Where:

a. $\mu(x)$denotes the fuzzy membership function,
b. $E_{trans}(i)$represents the transmission energy of the $i^{th}$base station,
c. $d(i)$represents the distance metric associated with the $i^{th}$base station.

The membership functions are defined using distance and energy criteria to evaluate the suitability of candidate base stations for efficient communication and energy management within the LTE access network.

**System Integration**

This involves the combination of various subsystems and components of the models in the design to cohesively function as one whole system. In the case of this study, the integration involves the combination of the cluster head processing model into the hierarchical energy optimization model in order to support the base station selection model which uses fuzzy logic algorithm for an optimized energy consumption and network efficiency. Figure 3 illustrates the cluster head processing and selection operation.

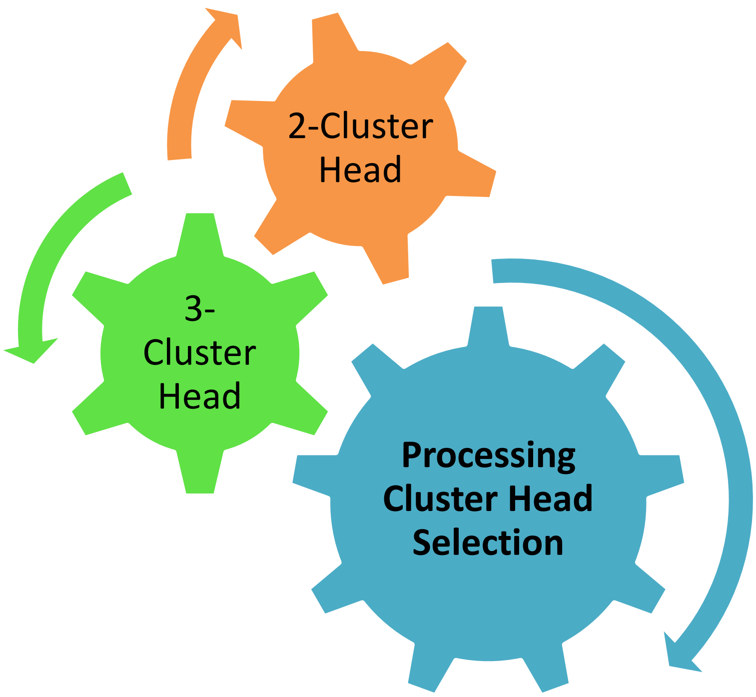


Figure 3: Cluster Head Selection Framework

The selection of cluster head as shown in figure 3 is a crucial step in the hierarchical routing protocol operation of an LTE network. The process determines the cluster head acting node that will be responsible for the management and coordination of communication in the respective clusters available in the network. The cluster head selection operation chooses a cluster according to the calculated highest probability of a cluster head being selected, cluster formation which join the nodes of the nearest cluster is performed. The cluster head selection operation is updated periodically based on the changes in network conditions. Figure 3 presents the integration of cluster selection operation into the routing protocol for the proposed energy saving algorithm for LTE operation.

**Cluster Formation**

a) The simulation results show that eNodeBs are grouped into clusters, with each cluster having a designated first-level cluster head.

b) First-level cluster heads manage local communication and data aggregation within their clusters.

**Hierarchical Management**:

a) Second-level cluster heads aggregate data from multiple first-level cluster heads, optimizing the communication paths and reducing the direct load on the BS.

b) This hierarchical approach improves network scalability and efficiency by distributing the management tasks.

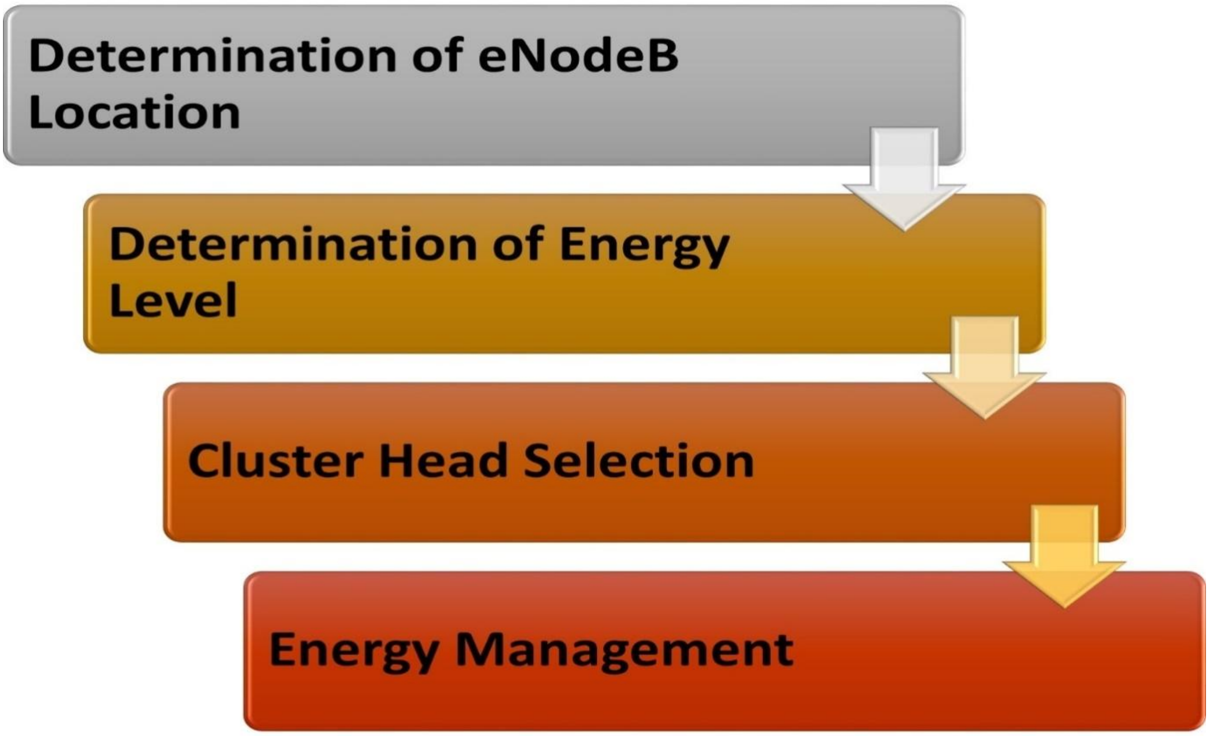


Figure 4: Hierarchical Energy Saving Block Diagram

The hierarchical operation of the system as shown in figure 4 starts with the determination of the eNodeB which involves obtaining the geographical information of the available eNodeBs before going on to determine the energy or battery power available to the nodes, which helps to know the operational capabilities and the roles on the nodes in the network. The cluster head selection operation reported in figure 3 is executed. Finally, the energy management process is executed which help to balance the energy consumption among the nodes and reduces resource wastages of the network, thereby extending the overall lifespan of the network. Furthermore, the next operation conducted in the system is the base station selection operation as shown in figure 5, where fuzzy logic model is implemented for optimal selection of base station.

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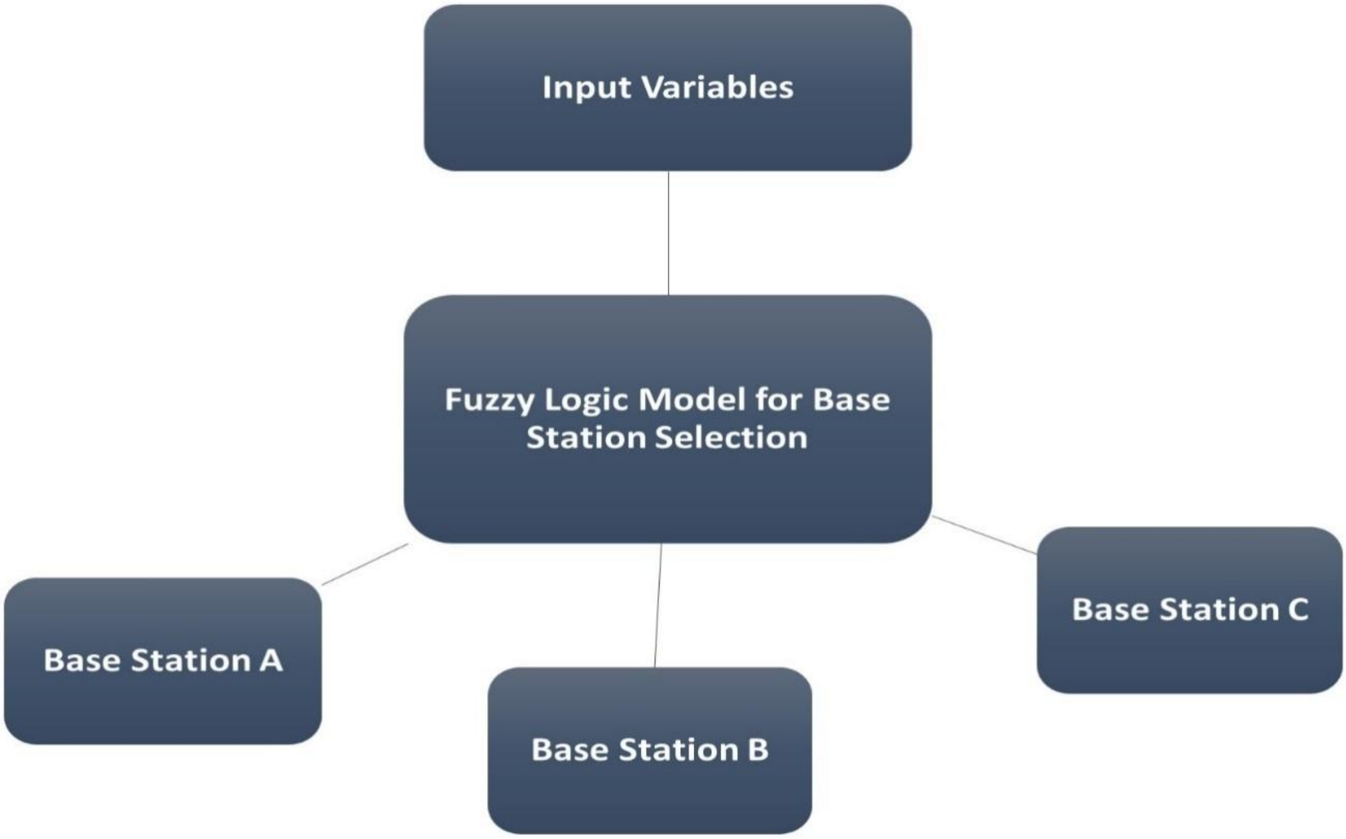


Figure 5: Base Station Selection Framework.

In figure 5, the framework for the selection of base station which involves the choice of the most suitable and appropriate base station which will serve as a user equipment according to different criteria such as capacity, load, signal strength and quality of service (QoS) requirements. The system adopts the fuzzy-logic based selection which evaluates multiple criteria such as QoS, user preferences, load and signal strength simultaneously in order to make intelligent and optimum decision while selecting the base station for operation. The integration of the different levels of operation in the system is illustrated in the block diagram presented in figure 6.

According to figure 6, the system operation starts at the network LTE environment which comprises of the eNodeBs, the cell structure, and the mobile stations. The core of each cell is where the stationary eNodeBs are situated. The locations of the mobile stations inside the LTE cellular environment are chosen at random. Next, using the array matrix (A) and cell radius (R), an eNodeB's X and Y coordinates in an LTE cellular environment may be found in respect to its nearby eNodeB. The next step is cluster formation which groups the nodes in clusters to form hierarchical structure within the network, then, cluster heads are selected according to criteria of energy level, communication capability and proximity to other nodes (distance).

The cluster heads then exchange aggregated data with associated CHs or transmit it to the base stations directly through the use of multi-hop communication.

**System Realization Sequence**

The fuzzy logic algorithm for optimum selection of target base station is implemented to evaluate the energy efficiency, capability and distance criteria necessary for selecting the most suitable base station within the cluster and ensuring efficient performance and energy consumption of the network. The output of the optimal base station selection is implemented to complete the intelligent and optimized decision making in selecting optimum target base station.

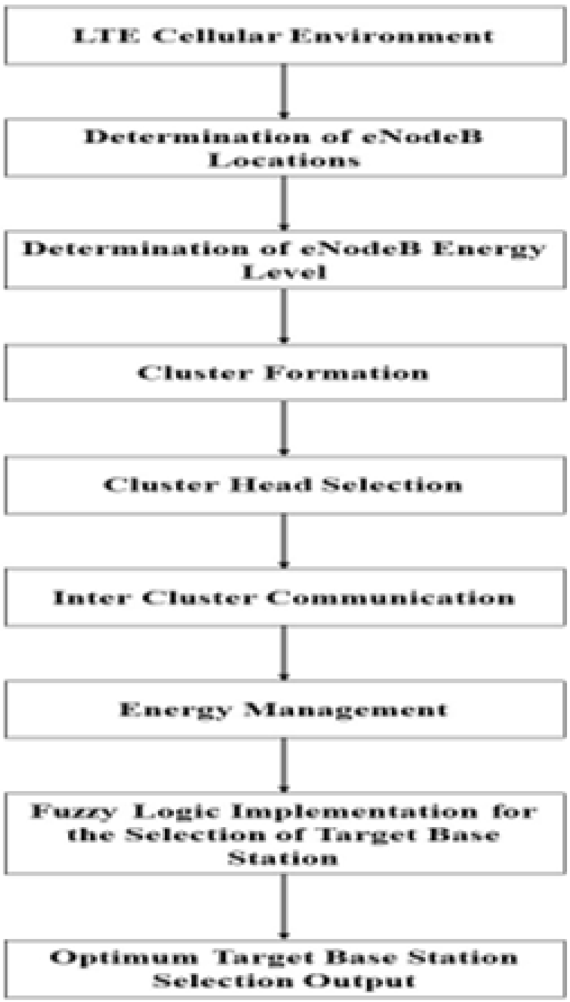


Figure 6: The Realization Sequence Block Diagram of the Enhanced Energy Efficient Model for Base Station Management

**Simulation parameter.**

The performance of the proposed dynamic energy-saving algorithm was evaluated using MATLAB simulations in a simulated LTE access network environment. The network consisted of 250 randomly distributed macro cells with an average of 100 active mobile stations per eNodeB and a distribution factor of 4. The base station (BS) was positioned at the origin $(0, 0)$.

A total of 400 simulation rounds were conducted for the non-hierarchical, first-level hierarchical, and second-level hierarchical scenarios. A radio energy model was employed to estimate the transmission energy required for cluster head selection, data aggregation, and data transmission. The initial energy of each node was set to 200 J.

Table 5: Simulation parameters:

| **Parameter** | **Value** |
|---|---|
| Initial energy of each node (Joules) | 200J |
| System Bandwidth | 20MHz |
| No of eNodeB | 250 |

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| | |
|---|---|
| Number of cluster head | 4 |
| Network Field Dimensions | 300m x 300m |
| Packet size (k) in bytes | 100Kb |

During cluster formation, cluster heads aggregated data from member eNodeBs and forwarded the aggregated information through the shortest path to the base station. Cluster head rotation was also implemented to balance energy consumption and extend network lifetime. The simulation parameters used in the study are presented in Table 5.

**Implementation of the Developed Multi- attributed Decision-making Fuzzy Logic Model on the Simulated LTE Access Network.**

A data routing environment for the LTE access network Gateway is provided by the suggested LTE access network performance enhancement. For the simulation of the suggested Protocol, MATLAB is utilised. MATLAB 7.11.0 (2010b) was chosen as the simulation tool to carry out the proposed methodology. A high-level technical programming language, MATLAB offers an interactive environment for developing algorithms, analysing, visualising, and calculating numbers.

With the help of MATLAB Simulink libraries, the multi-attribute decision making model seen in figure 7 was created. The number of cluster heads, the transmission distance, the energy of the neighbouring eNodeB, and the energy level of a node were all determined by the model using a bunch of decision boxes (if else tool boxes).

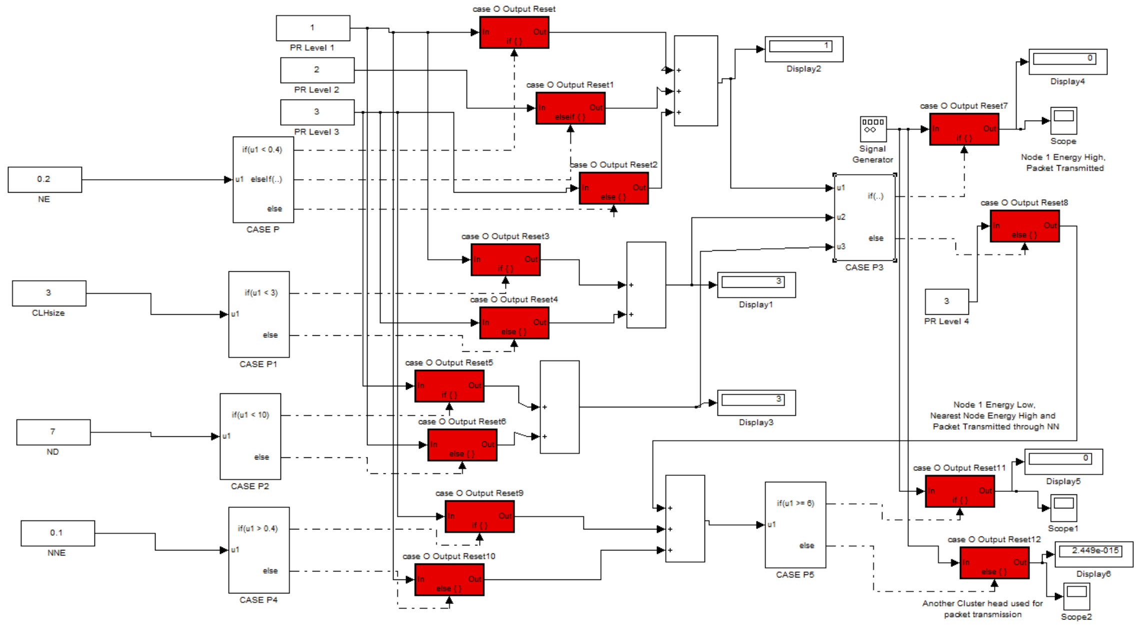


Figure 7: MATLAB Model of Multi- attributed Decision-making Fuzzy Logic Model on the Simulated LTE Access Network.

Variable parameters are captured by the constant box in the model. The transmitting node for the packet is determined by the value supplied in the parameter box (NE, Cluster Head size, ND, and NNE).

The created MATLAB GUI is seen in figure 7. The text boxes on the user interface are how the GUI receives inputs. The GUI feeds the inputs to the collection of MATLAB functions that carry out the necessary operations when the proper inputs are supplied and the desired button is pressed. A user-friendly simulation tool (GUI) was developed to evaluate how much energy an LTE network can save using dynamic scheduling techniques. The analysis was carried out by varying how energy consumption responds to traffic load, while maintaining a fixed level of service quality.

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## RESULTS AND DISCUSSION

The non-hierarchical routing technique's topology, shown in figure 8, allows all eNodeB transmissions to go straight to the BS.

Figure 8 (Conceptual):

1. Base Station (BS): Located centrally in the diagram.
2. eNodeBs: Multiple eNodeBs are positioned around the BS, each with a direct link (line) connecting them to the BS.
3. No Intermediary Nodes: There are no intermediate nodes or layers; all connections are direct between eNodeBs and the BS.

This conceptual diagram illustrates the simplicity and directness of the non-hierarchical routing technique.

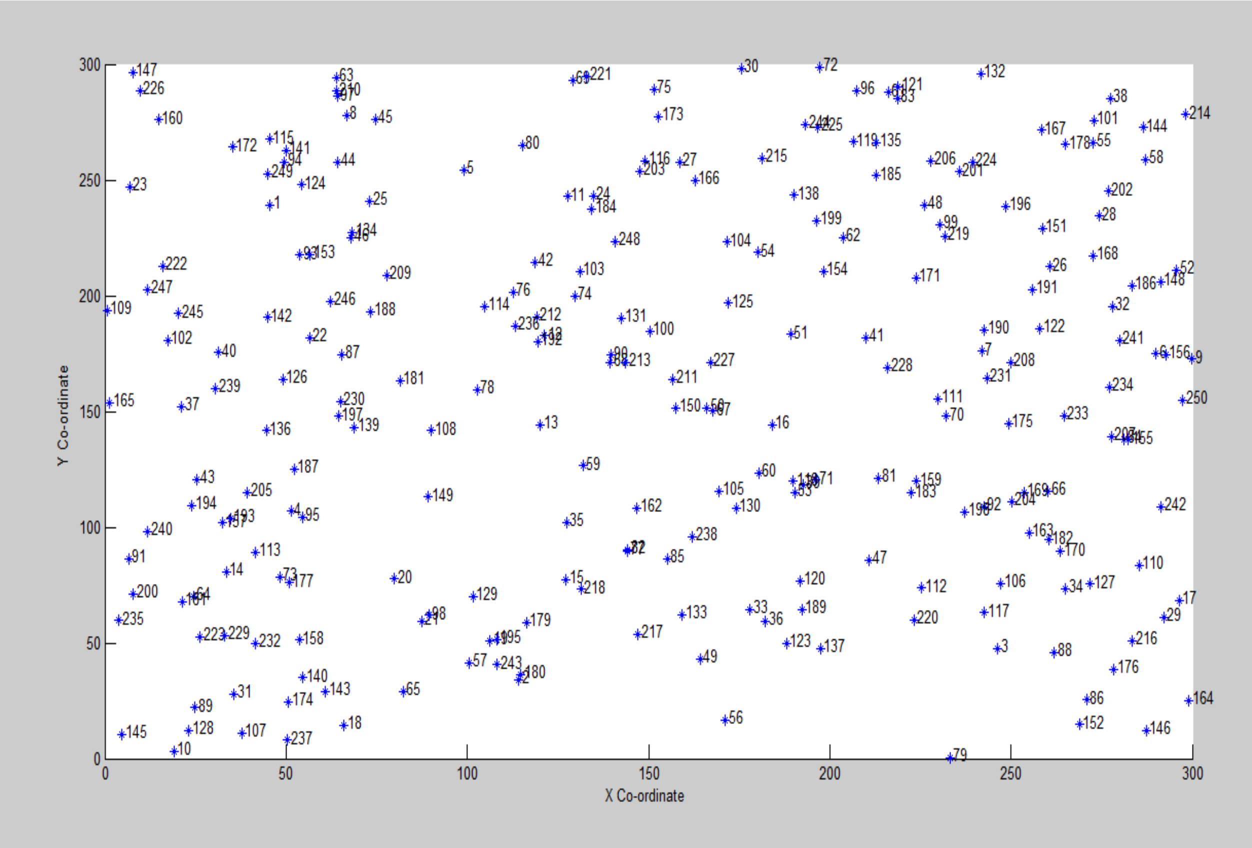


Figure 8: Simulation Result for one Cluster head (Non hierarchical formation)

Table 6: Comparison of Mean Value of the Residual Energy:

| **Technique** | **Mean residual energy (J)** |
|---|---|
| Non-hierarchical Technique | 8.2300 |
| 2 CH-hierarchical routing | 11.1541 |
| 3 CH-hierarchical routing | 49.2187 |

The simulation carried out in MATLAB Simulink produced the results of the base station selection with the fuzzy logic model. The eNodeB in the network are formed into clusters of different sizes of one, two and three.

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One indicates a non-hierarchy formation of cluster, two and three indicate different level of hierarchy, one and two respectively for data transmission. Figure 8 indicates the non-hierarchical structure of the routing technique.

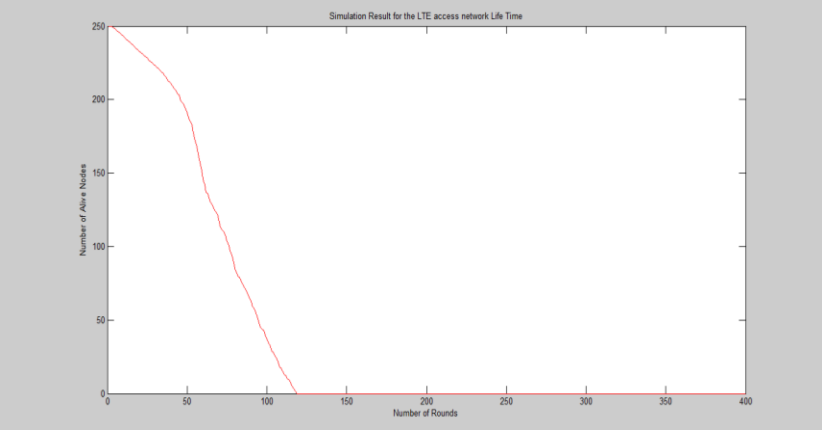


Figure 9: Simulation Result for Network lifetime when one cluster head is used (number of alive nodes for a particular round of simulation).

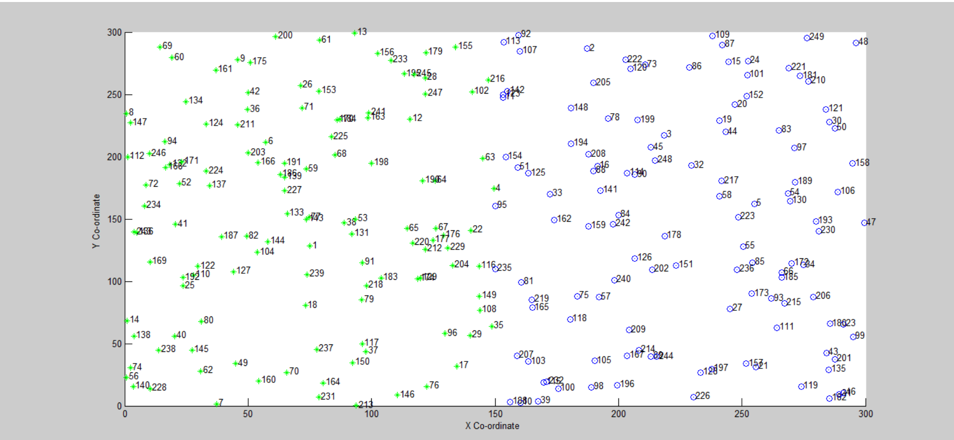


Figure 10: Simulation Result for two Cluster head (hierarchical formation)

Figure 10 shows the simulation result of the cluster formation where two cluster head hierarchies was used which are represented by two different colours.

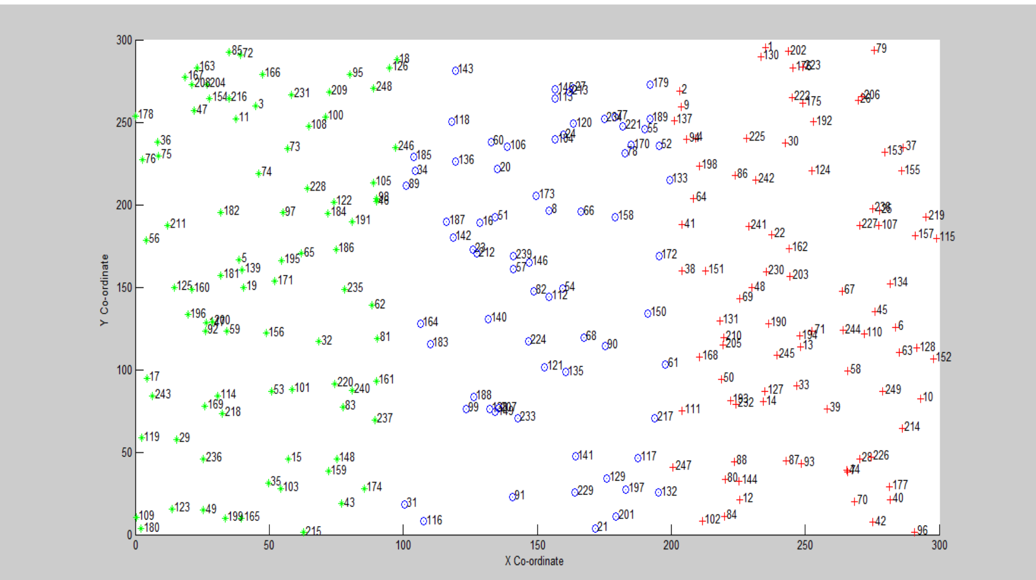


Figure 11: Simulation Result for three Cluster Head (hierarchical formation).

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The results of the cluster creation simulation are displayed in figure 11 which shows three distinct colours corresponding to the three cluster head hierarchies that were employed.

Table 7: Network Distance Vs Number of Clusters:

| **Distance from Bs in m** | **Cluster head size 1** | **Cluster head size 2** | **Cluster head size 3** |
|---|---|---|---|
| 150 | 7.2666 | 7.9959 | 9.0006 |
| 160 | 6.3214 | 6.7841 | 7.3659 |
| 170 | 5.5584 | 5.8652 | 6.2291 |
| 180 | 4.9312 | 5.1416 | 5.3815 |
| 190 | 4.4078 | 4.5561 | 4.7206 |
| 200 | 3.9657 | 4.0727 | 4.1889 |
| 210 | 3.5884 | 3.6671 | 3.7512 |
| 220 | 3.2634 | 3.3223 | 3.3844 |
| 230 | 2.9814 | 3.0260 | 3.0728 |
| 240 | 2.7348 | 2.7692 | 2.8049 |
| 250 | 2.5180 | 2.5447 | 2.5723 |

The results presented in figure 12 demonstrate the impact of the fuzzy logic cell selection model on the dynamic formation of clusters in the cellular network. The fuzzy logic model, integrated into the cell selection process, plays a crucial role in determining the optimal number of clusters for various distances from the base station through its energy level prediction. As evident in the graph, the number of clusters exhibits a consistent decrease as the distance from the base station increases. Notably, this trend remains consistent across different cluster head-set sizes, ranging from size 1 to size 5.

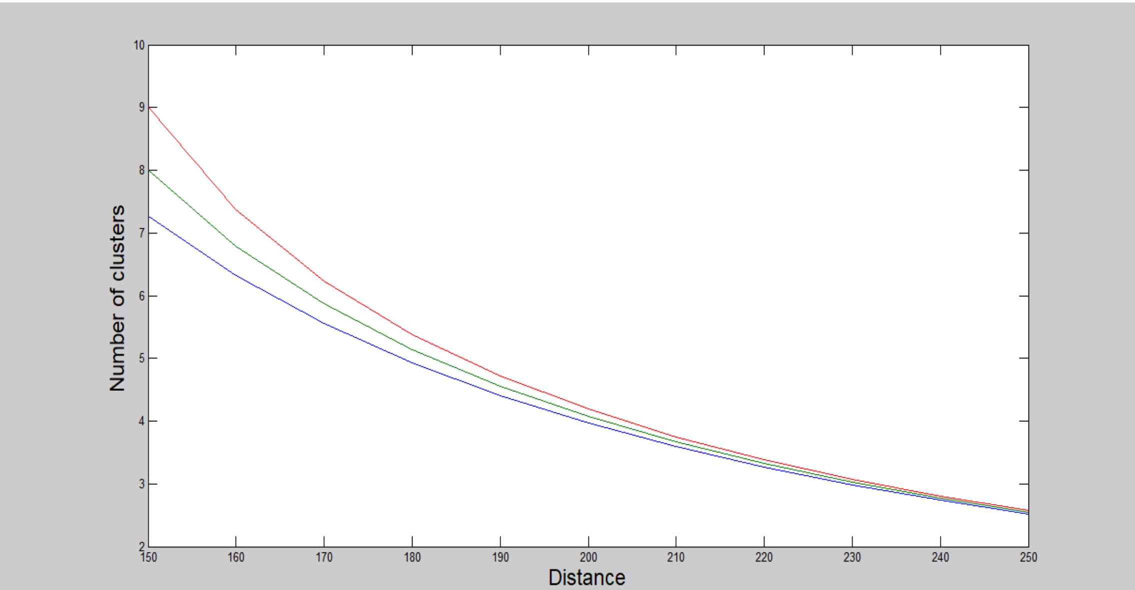
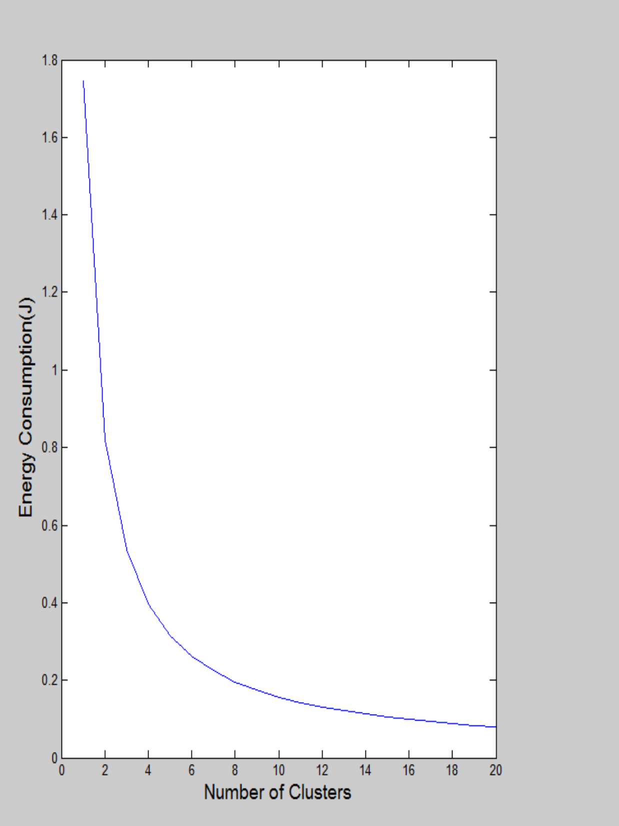



Figure 12: Distance from Bs Vs Number of Clusters

This uniformity implies that the cluster head-set size is not directly influenced by the distance from the base station as can be seen in table 7. Instead, the fuzzy logic cell selection model dynamically adjusts the number of clusters to optimize energy consumption at the eNodeB. The observed correlation between distance and cluster count underscores the efficiency of the fuzzy logic-based approach in adapting the network topology to the varying spatial requirements, thereby influencing energy consumption patterns in a manner conducive for overall system performance. The figure 13(a and b) presents the relationship between the number of clusters, energy consumption, and cluster head-set sizes is vividly portrayed, showcasing the application of fuzzy logic in cell selection based on the energy levels of the cells.



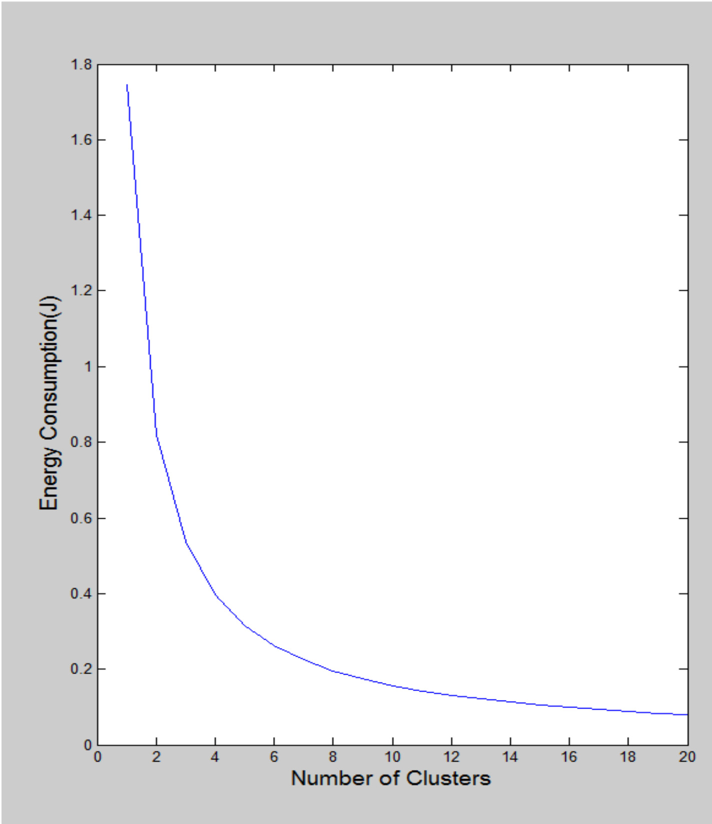




Figure 13a Figure 13b

Figure 13 (a and b): Number of Clusters Vs Energy Consumption for various cluster head-set sizes.

In figure 13a, where the cluster head-set size is 1, the energy consumption demonstrates a noticeable reduction as the number of clusters increases. The optimal energy consumption range, between 0 and 6 Joules, suggests a favorable performance when the network is configured with a single cluster head. Conversely, in figure 13b, depicting a cluster head-set size of 3, the energy consumption similarly decreases with an optimal variation between 0 and 1.8 Joules. Notably, the energy consumption in figure 13b is approximately three times lower than that in figure 13a when the cluster head-set size is 1.

Table 8: Comparison of Energy Consumption:

| Number of transmissions | Energy level (Non -hierarchical routing) | Energy level (2 CH-hierarchical routing) | Energy level (3 CH-hierarchical routing) |
|---|---|---|---|
| 1 | 250 | 250 | 250 |
| 25 | 228 | 250 | 250 |
| 50 | 191 | 250 | 250 |

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| | | | |
|---|---|---|---|
| 75 | 103 | 249 | 246 |
| 100 | 37 | 219 | 222 |
| 125 | 0 | 179 | 195 |
| 150 | 0 | 149 | 169 |
| 175 | 0 | 130 | 147 |
| 200 | 0 | 5 | 129 |
| 225 | 0 | 0 | 97 |
| 250 | 0 | 0 | 75 |
| 275 | 0 | 0 | 53 |
| 300 | 0 | 0 | 45 |
| 325 | 0 | 0 | 0 |
| 350 | 0 | 0 | 0 |
| 375 | 0 | 0 | 0 |
| 400 | 0 | 0 | 0 |

This stark contrast emphasizes that a larger cluster head-set size, determined through fuzzy logic cell selection considering energy levels, correlates with significantly lower energy consumption during transmission. These outcomes align with the objectives of the fuzzy logic-based approach, which aims to optimize cluster configurations for reduced energy consumption based on the energy levels of the cells. The observed reduction in energy consumption not only enhances the network's operational efficiency but also extends its lifetime, facilitating a greater number of transmissions within the network.

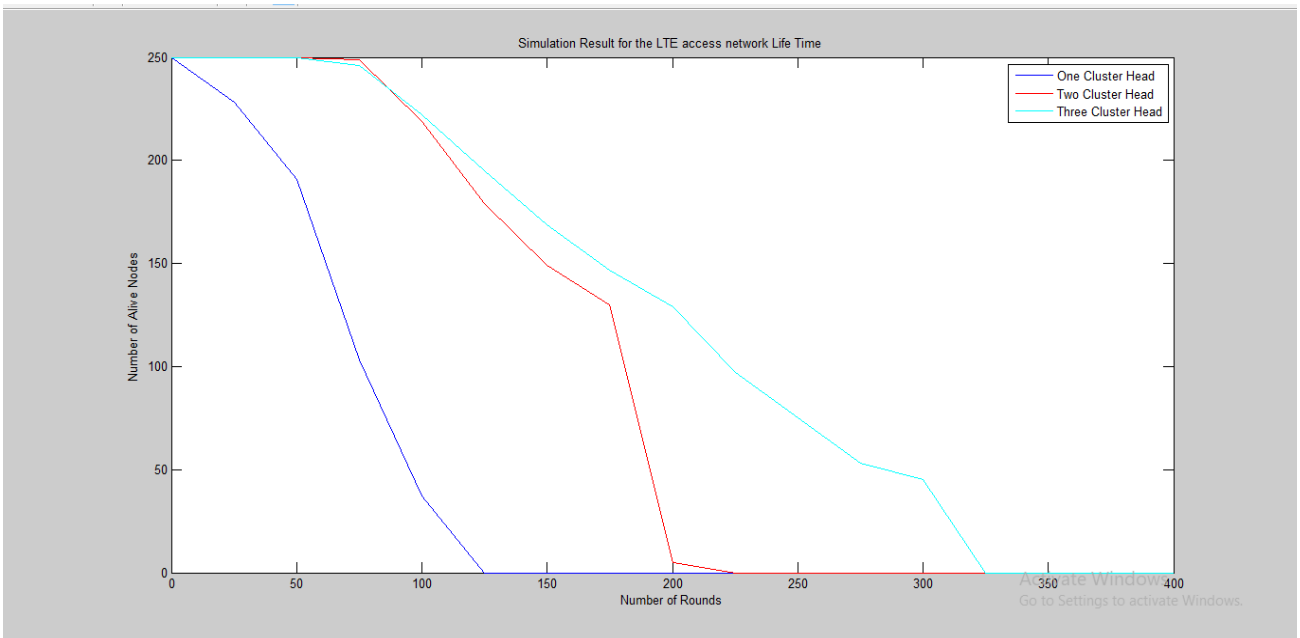


Figure 14: Comparing the lifespan of a network with one, two, or three cluster heads using simulation results

In contrast to the suggested method, figure 14 shows that the non-hierarchical methodology (one cluster head) network entirely stopped working at an earlier simulation cycle. The functional capacity of the first level hierarchical approach (two cluster heads) lasted until 200 rounds, while the second level hierarchical approach lasted until an estimated value of 330 rounds of simulation. It is observed that the non-hierarchical network's functional capacity lasted until an estimated value of 120 simulation rounds. Moreover, figure 14 shows that under the three-cluster creation scenario (second level hierarchy), the network lifespan grew to a given length. When comparing this increase to the two-cluster formation and one cluster formation approach, the LTE access network lifespan was further extended.

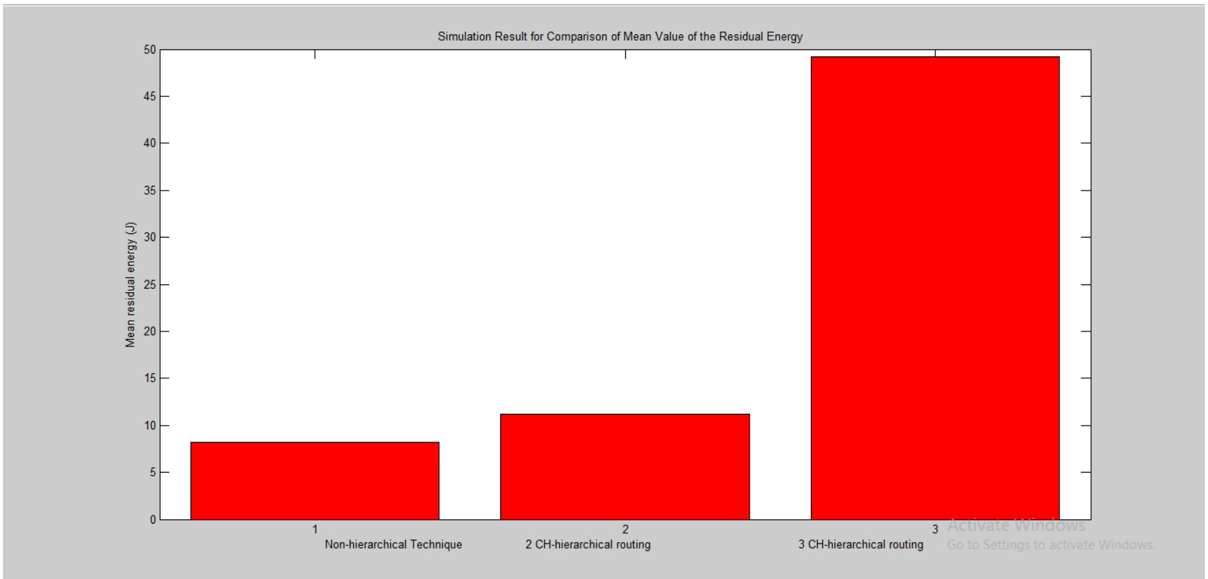


Figure 15: Bar chart of residual energy for non-hierarchical and hierarchical technique

Figure 15 illustrates a bar chart comparing residual energy between non-hierarchical and hierarchical techniques. The mean residual energy for both techniques over 400 simulation cycles is detailed in Table 8. As the hierarchical structure increases, the mean residual energy also rises, indicating enhanced network performance. Notably, eNodeBs possess more energy at higher hierarchical levels, suggesting improved efficiency. This study, conducted through MATLAB Simulink simulations, provides insights into energy management within LTE access networks. eNodeBs are organized into clusters, ranging from non-hierarchical to two and three hierarchical levels for data transmission. Furthermore, figure 15 highlights the performance contrast between hierarchical and non-hierarchical methodologies.

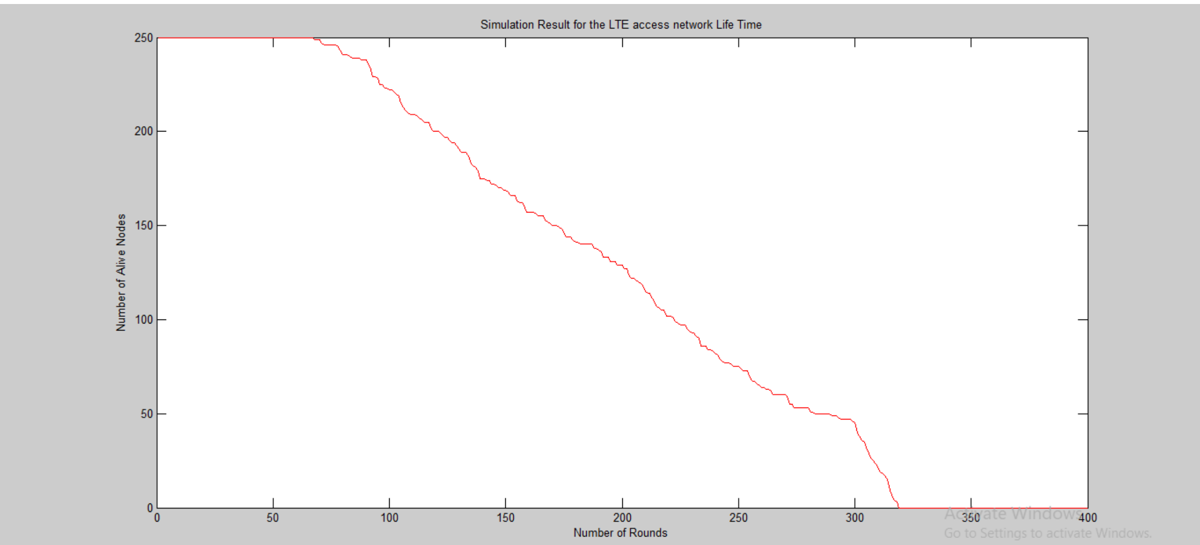


Figure 16: Simulation results for the network lifespan using three cluster heads (the total number of active nodes during a certain simulation cycle)

While the non-hierarchical approach experiences early network failure, hierarchical methods demonstrate prolonged functionality, with the second-level hierarchy achieving 36.6%. energy efficiency over 330 simulation rounds as can be seen in figure 16.

Overall, the hierarchical routing strategy, particularly with three cluster heads, exhibits superior network performance and energy efficiency of 52.5%, extending the lifespan of LTE access networks compared to non-hierarchical approaches.

## CONCLUSION

Persistent failures in communication networks, leading to service degradation and disruption of business activities, are significantly influenced by high operational costs associated with inefficient and unstable energy consumption in 4G broadband systems, although other technical and infrastructural factors also contribute to network unreliability. Excessive energy usage at base stations significantly increases expenditure on power generation, backup systems, and maintenance, thereby undermining network reliability and quality of service. To mitigate these challenges, this study developed and implemented an enhanced energy-efficient base station management model for 4G broadband systems**,** leveraging hierarchical routing and fuzzy logic algorithms to reduce energy consumption, lower operational costs, and improve overall network performance.

The research methodology involved the design of a fuzzy logic–based algorithm for optimal target base station selection, alongside the development of a hierarchical routing algorithm aimed at improving energy efficiency within the LTE access network. The energy savings achieved through the proposed algorithms were systematically evaluated, and a SIMULINK-based model was designed for simulation, analysis, and validation of energy efficiency performance in the LTE access network.

Simulation results demonstrate a significant improvement in energy efficiency. The mean residual energy recorded for the non-hierarchical technique was 8.2300 J, whereas the fuzzy-based two-cluster-head (2-CH) hierarchical routing technique achieved a mean residual energy of 11.1541 J. This represents a 36.6% enhancement in energy efficiency when the fuzzy-based hierarchical algorithm was integrated into the base station management system. Based on the acquired results, compared to the non-hierarchical approach, network lifespan improved by 52.5% in the three-cluster creation scenario (second level hierarchy).

Overall, the findings confirm that the proposed fuzzy-based hierarchical energy management model substantially enhances energy utilization in 4G LTE networks, thereby improving network reliability, reducing service disruptions, and supporting sustainable broadband communication infrastructures.

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