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A GAME-THEORETIC CLUSTERING FRAMEWORK FOR ENHANCING ENERGY EFFICIENCY AND THROUGHPUT IN GSM NETWORKS

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ABSTRACT
The increasing density of users, constraints on energy resources, and heightened radio interference in GSM networks have made the need for intelligent, adaptive methods to optimize clustering structures more apparent than ever. Traditional methods like LEACH and K-Means have limited effectiveness in real-world scenarios due to their lack of consideration for network dynamics, the rational behavior of nodes, and traffic variations. This paper proposes a game theory-based method as a novel approach, aiming to optimize cluster head selection, reduce energy consumption, and enhance link quality under variable network conditions. To evaluate the performance of the proposed method, a comprehensive simulation framework was designed, comparing four clustering methods—Game Theory, LEACH, K-Means, and Random—under identical conditions. The evaluation was based on multiple metrics, including energy consumption, average SINR, spectral efficiency, throughput, cluster stability, and network lifetime. The simulation results demonstrate that the proposed game theory-based method outperforms the others in most metrics. By modeling user interactions as a repeated game and gradually updating the payoff function, this method achieves a 25% to 35% reduction in energy consumption, a 7 to 12 dB increase in average SINR, a 15% to 25% improvement in packet delivery rate, a significant enhancement in spectral efficiency, and a 1.5 to 1.8 times increase in network lifetime compared to conventional methods. Furthermore, the cluster structure in the proposed method exhibits greater stability, minimizing sudden changes in cluster head selection. These results highlight the superiority of the proposed approach.

KEYWORDS: GSM Networks, Clustering, Game Theory, Energy Efficiency, SINR, Spectral Efficiency, Packet Delivery Rate, Network Lifetime.

1- INTRODUCTION

The cellular telephone networks over the past two decades, despite the introduction of new generations such as LTE, 5G, and Ultra-Dense Networks, still rely extensively on GSM network infrastructures[1]. Due to their simplicity, low cost, wide geographical coverage, and support for a broad range of devices, these networks continue to serve as the backbone of cellular communications in many developed countries and especially in developing nations. Despite the resilience and widespread adoption of this technology, one of the significant challenges in GSM networks is high energy consumption and inefficient traffic load management at Base Transceiver Stations (BTS). Field evidence indicates that BTS units account for over 60 to 70 percent of the network's total energy consumption, even during periods when traffic is practically very low or near zero[2-4]. This issue not only increases operational costs for operators but also creates considerable environmental impacts. Optimizing energy consumption in cellular networks is typically pursued through strategies such as periodic BTS sleep modes, transmission power adjustment, dynamic radio resource management, and intelligent traffic load allocation. However, one method that has gained significant attention from researchers in recent years is base station clustering. Clustering, as a technique for grouping nodes based on criteria such as geographical distance, interference patterns, traffic load levels, or energy conditions, can lead to reduced energy consumption, improved throughput (Thr), decreased processing load, and enhanced resource efficiency [5-7].

Despite the widespread use of clustering in wireless sensor networks, ad-hoc networks, and IoT networks, applying this concept to GSM networks comes with its own set of challenges. This is because, in GSM architecture, base stations operate independently, and direct data sharing or group coordination is not inherently part of the original standard[8]. Therefore, clustering needs to be implemented as an algorithmic layer at the network management level. Furthermore, selecting the Cluster Head (CH) and determining the membership of BTS units in different clusters is a complex process. Each BTS has distinct characteristics, constraints, and objectives, and the decision of one affects the decisions of others[9, 10].

In this context, game theory serves as a powerful mathematical tool for modeling decision-making interactions among autonomous entities, offering a suitable approach for analyzing BTS behavior in such a scenario. From a logical perspective, each BTS can be considered a player that decides, based on its own payoff, whether to become a CH, join a cluster, or enter a low-power (sleep) state. This payoff could be a combination of metrics like Thr, energy consumption, interference, link capacity, and the status of neighboring stations. The decision of each BTS influences the payoffs of others, and ultimately, the network converges to a stable state (a Nash equilibrium) where no base station has an incentive to change its strategy[11-13].

Although several studies in recent years have utilized game theory in areas such as power allocation, interference control, and cellular resource management, the simultaneous use of graph-based clustering and game theory for optimizing energy and Thr in GSM networks still represents a significant gap in the research literature[14]. Most existing studies have focused on newer generation networks, while GSM, due to its perceived age and assumed lack of need for optimization, has received less attention. This is despite the fact that millions of BTS units remain active worldwide, and even minor energy improvements in GSM networks could lead to substantial global savings[15-17]

The proposed approach of this paper is to establish a game theory-based clustering framework where BTS units form stable clusters based on graphical interactions and performance criteria. In this framework, the GSM network is first modeled as a graph, with nodes representing BTS units and edges representing neighbor or interference relationships. Then, a non-cooperative game is defined in which each BTS selects its optimal strategy based on its own payoff function. Strategies include becoming a CH, joining a cluster, remaining independent, or entering a sleep state. The payoff function is a weighted combination of Thr, energy consumption, and interference. Given the nature of the game and the defined payoff function, the system converges towards clusters with Nash stability, where the decisions of the BTS units are both optimal and compatible with the network.

The proposed framework offers several key advantages over classical clustering methods, including distributed and local decision-making, reduced need for central control, dynamic cluster adaptation to changes in load and energy, logical and self-regulating CH selection, significant network energy reduction, and improved Thr with reduced congestion and load management.

Due to its foundation in graphical interactions, this framework is well-suited for deployment on GSM networks and does not require hardware changes. Furthermore, its design allows for future extension to LTE or 5G networks [18]. Since energy consumption in cellular networks is a primary research topic in telecommunications and load management in legacy networks remains a real challenge for operators, the model presented in this paper can make an effective contribution to improving the efficiency of operational networks.

In summary, this paper presents an innovative framework that combines graph-based clustering and game theory to reduce energy consumption in BTS units while also improving network Thr. The innovations of this research are:

- A game theory-driven clustering framework for the distributed decision-making of BTS units in forming optimal clusters.
- Simultaneous energy/Thr optimization through interactive BTS management.
- Graphical modeling of the GSM network to provide a stable solution for legacy cellular architectures.

The remainder of this paper is organized as follows. Section II reviews the research background in the fields of energy and Thr optimization in cellular networks. Then, in Section III, the GSM system model and the proposed method are presented. Section IV will present the results and a comparative performance analysis of the proposed method. Finally, a conclusion and suggestions for future research in this area will be provided.2-Related works

2- RELATED WORKS

In a CoMP scenario, the problem of putting base stations to sleep is modeled as a sequential decision-making process, using multi-stage Q-learning to determine the sleep state of cells. The goal of this method is to reduce the power consumption of BSs while maintaining downlink performance and user QoS levels. Simulation results show that the policy derived from Q-learning, compared to simple threshold-based methods, simultaneously increases Energy Efficiency (EE) and improves network Thr [19].

In [20], working in a heterogeneous network with relays and D2D communications, formulated the problem of maximizing the network rate-to-energy consumption ratio as a nonlinear fractional program. Using the Charnes–Cooper transformation and the Outer Approximation method, they achieved an ε-optimal solution for parameters like power, spectrum allocation, and cell selection, demonstrating a significant improvement in EE compared to baseline schemes.

In refrence [21] proposed a self-organizing system for D2D-based heterogeneous networks, where the MAC and physical layers are jointly and adaptively configured to reduce energy consumption and increase spectral efficiency. By modeling user and cell behavior as a game and applying dynamic policies, this framework reduces energy per bit while maintaining capacity and QoS levels.

In [22] suggested a cell sleep strategy for dense heterogeneous networks, based on clustering BSs according to an interference graph. In this approach, graph nodes represent base stations and edges represent strong interference between them. By putting lightly loaded clusters to sleep and reconfiguring coverage areas, energy consumption is reduced while overall network Thr and QoS constraints are maintained.

In [23] formulated the power control problem in multi-cell networks as a multi-agent reinforcement learning problem, where each link is considered a DRL agent. Using a shared neural architecture and simultaneous updates, their proposed method can optimize the sum network rate in the presence of interference. Comparisons with methods like WMMSE show that this algorithm provides a higher rate with lower energy consumption for a target rate [20].

Paper [24] presented a centralized DRL framework for resource allocation in next-generation networks, aiming to optimize a utility function that combines EE and Thr. The problem is modeled as an MDP, and a DQN agent learns how to allocate spectrum and power by observing power status, load, and channel conditions. Results indicate that this method achieves higher EE than convex optimization-based solutions while preserving or even improving network Thr.

In paper [25] developed a DRL-based framework for the joint optimization of power allocation and user association in heterogeneous networks. Here, the state includes BS load, channel quality, and link status, and the DQN agent selects the BS and power level for each user to maximize total EE. Results demonstrate the superiority of the proposed method over heuristic algorithms in terms of both EE and user rates.

In [26] in the context of fifth-generation RAN slicing, proposed the EE DRL RA algorithm. In this framework, a large-timescale DL network determines the resource amount for each slice, while a small-timescale DRL agent performs fine-grained power and radio resource allocation. The proposed hierarchical structure not only maintains functional isolation between slices but also enhances EE and network capacity.

In [27], to solve the power allocation and user association problem in fifth-generation HetNets, introduced a Multi-Agent Parameterized DRL (MA PDRL) approach. In this method, the action space includes continuous power and discrete BS selection. Results show that MA PDRL outperforms WMMSE, non-cooperative games, and traditional DRL in terms of EE, sum rate, and the percentage of users with satisfactory QoS.

In [28] introduced an adaptive and low-power eICIC scheme for H-CRAN, where a DRL agent is responsible for adjusting Almost Blank Subframe scheduling and power parameters based on load and interference conditions. The reward function consists of EE and QoS metrics, and results indicate that this scheme consumes less energy while achieving higher spectral efficiency and user Thr compared to static eICIC versions.

In [29] designed an energy-aware federated deep reinforcement learning mechanism for beyond-5G networks. In this structure, BSs train resource allocation policies in a distributed manner, exchanging only gradients with a central server. With a well-designed reward function, both EE and mobile user QoS are maintained, while energy consumption and signaling overhead are reduced.

In paper [30] investigated radio resource scheduling in 5G networks using DRL. The state includes traffic queues, channel conditions, and user service priority, and the DRL agent maximizes the sum rate under maximum delay constraints by selecting RBs and users. This method provides higher Thr and lower delay compared to classic schedulers like PF and MLWDF.

In [31]proposed a distributed multi-agent DRL algorithm for power control in cellular networks, where each BS is trained as a local agent. By exchanging limited information, the agents learn policies that reduce inter-cell interference, guarantee link quality, and lower energy consumption. Results show this method increases EE without a significant reduction in user rates.

In [32] in relay-assisted D2D networks, analyzes the relay selection and resource allocation problem with a focus on increasing EE while maintaining Thr. Combining analytical modeling with optimization algorithms shows that optimal relay selection and the joint allocation of power and bandwidth can significantly improve the EE and capacity of D2D users.

The comparison presented in Table 1 among recent studies shows that most research has focused on a specific dimension; typically, they have either used only reinforcement learning for energy and Thr optimization, or have solely pursued optimization-based and power control approaches. In some works, although reducing energy consumption and increasing data rate have been targeted, they lack components such as structured clustering, graph modeling, or stability analysis based on interactions among base stations. Some studies have considered clustering or graphs, but they do not incorporate the aspect of decision stability and inter-cell interactions that are guaranteed by game theory. Another important point is that most research has concentrated on 5G networks, HetNet, or D2D scenarios, while the needs of GSM networks—despite their continuing infrastructural role—have been less systematically examined. In contrast, our proposed framework has been able to bring together key elements including graph modeling, clustering based on base-station interactions, stability assurance via game theory, and simultaneous energy-Thr optimization within a unified architecture compatible with GSM. This coherent and gap-filling combination makes the presented method more comprehensive, more practical, and conceptually stronger than previous works.

Table 1: Comparison of Previous Studies and the Proposed Research

Ref	(RL/DRL)	Game theory	Graph modeling	EE	Thr (Thr)	Clustering	GSM
[19]	✓			✓	✓		
[20]				✓	✓		
[21]		✓		✓			
[22]			✓	✓	✓	✓	

[23]	✓			✓	✓		
[24]	✓			✓	✓		
[25]	✓			✓	✓		
[26]	✓			✓	✓		
[27]	✓			✓	✓		
[28]	✓			✓	✓		
[29]	✓			✓	✓		
[30]	✓				✓		
[31]	✓			✓	✓		
[32]				✓	✓		
Proposed method		✓	✓	✓	✓	✓	✓

3- PROPOSED METHOD

Figure 1 illustrates the system model of the proposed method. The proposed system model presents a distributed framework for the simultaneous optimization of energy efficiency and throughput in GSM networks, based on graph modeling and non-cooperative game theory. The network is represented as an undirected graph G=(V,E), where nodes represent BTSs and edges represent interference interactions and communication constraints. Each base station only has access to local information, including traffic load, received interference, channel quality, and its own power status, and signaling exchange is performed only with neighboring nodes. This eliminates the need for centralized coordination and enables fully distributed decision-making. Decisions are made in discrete, synchronized time intervals to prevent momentary fluctuations in service due to potential changes in the operational status of BTSs. Based on this structure, base stations are dynamically organized into independent clusters, with each cluster having a CH whose role is solely local coordination, not centralized management. Relying on its own local information, each BTS selects the optimal strategy for cluster membership, role change, or operational status adjustment to maximize a utility function that includes energy, interference, and throughput metrics. This mechanism forms a stable non-cooperative game in which a Nash Equilibrium guarantees the stability of the cluster structure and the optimality of decisions under real-world, heterogeneous network conditions.

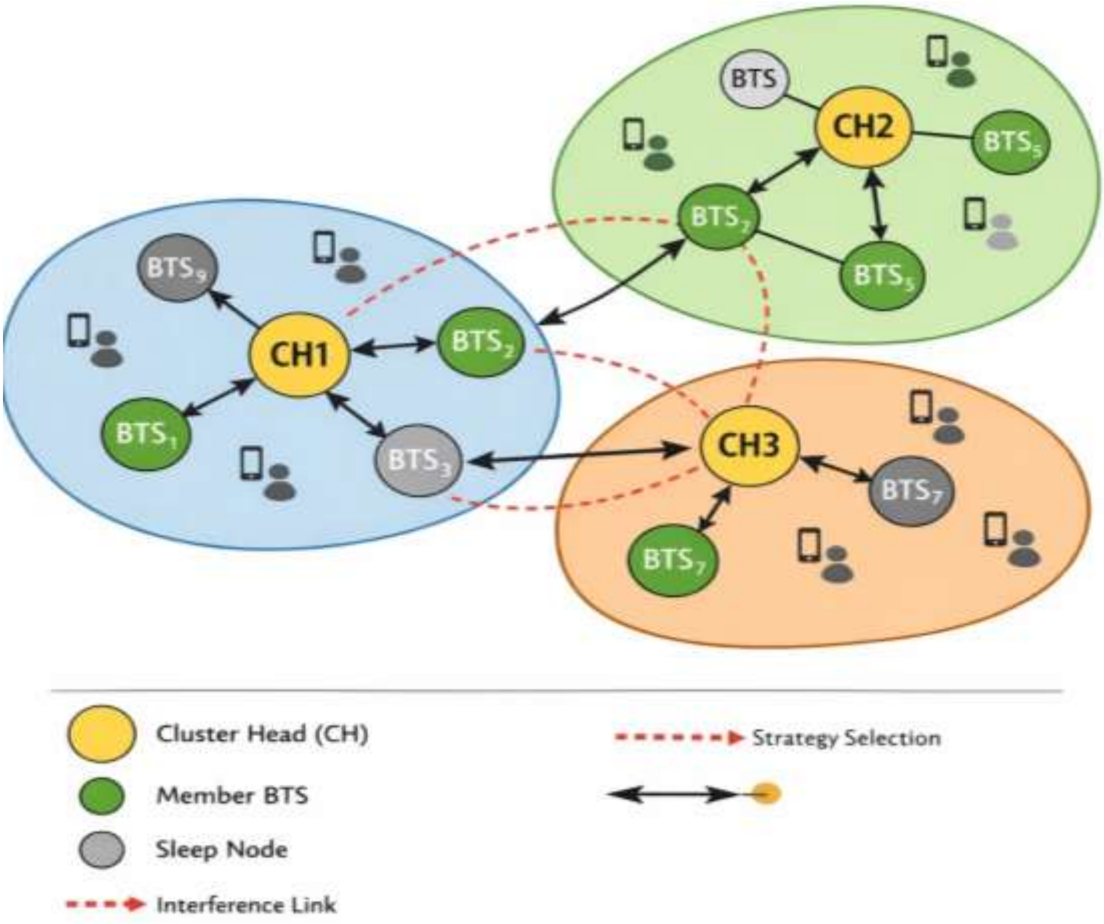

Figure 1. The Research System Model

1-3. The Proposed Distributed Clustering Game Method

In this approach, fully distributed clustering is employed as the primary operational mechanism of the network. Each working cycle consists of two phases: the Setup Phase and the Stable Phase. In the Setup Phase, the network organization process is carried out through cluster formation and CH selection to establish a suitable operational structure. Subsequently, in the Stable Phase, nodes exchange their data according to the established clustering—a process designed to reduce energy consumption and improve overall network efficiency.

• Setup Phase

In the cluster setup phase, the CH selection process is based on a set of spatial and energy criteria to ensure clusters are formed optimally across the network. First, a distance constraint between CHs is applied; meaning two CHs cannot be located within a specified spatial threshold. This condition prevents cluster overlap and leads to a uniform and stable distribution of CHs throughout the network. Furthermore, the residual energy level of each node is considered a decisive indicator, and only nodes with energy above a certain threshold are eligible to serve as CHs. Nodes with a higher number of neighbors—and thus a greater capacity for data aggregation—are given higher priority. Additionally, a shorter distance to the BS is considered a key criterion, as closer nodes require less power for data transmission, thereby reducing the network's energy cost. Ultimately, the selected CHs act as intermediaries between member nodes and the base station, facilitating efficient data transfer with minimal energy overhead.

$$E(s_i) > \beta_{opt} \times E_{to\,sin\,k} \tag{1}$$

$$\beta_{opt} = (v_{max} - r) r_{max} \times (E_{to\,sin\,k} |E.(s_i))| \tag{2}$$

$$N(s_i) > N_{Neighbours} \tag{3}$$

$$D(s_i) < DS_{Neighbours} \tag{4}$$

In this model, S_i represents the residual energy of the *i-th* node. The $E_{to\,sin\,k}$ denotes the energy required to transmit data directly from any node to the base station (BS). The parameter β_{opt} specifies the maximum data volume that node S_i can transmit to the BS. The total number of protocol execution cycles is represented by r_{max}. Furthermore, $N(s_i)$ indicates the number of neighboring nodes of candidate node i for the CH role, and $N_{Neighbours}$ shows the total number of neighbors for that node. The distance of candidate node iii from the base station is specified by $D(s_i)$, and $DS_{Neighbours}$ represents the average distance of that candidate's neighboring nodes to the BS.

• steady- state Phase

 Data Operations and Energy Management: During the stable phase, cluster member nodes transmit their data, while the CH performs data aggregation and monitors the energy consumption and residual energy of each node. This enables optimized energy management at the cluster level.

 Estimating the Number of Neighbors for the CH: In this step, the CH calculates the number of cluster members and neighboring nodes. This determines the density and volume of communication traffic it must manage.

 Calculating the Distance from the CH to the Base Station (BS): The communication distance between each CH and the BS is determined. This distance directly impacts the energy required for data transmission and plays a crucial role in optimizing energy consumption.

 Applying Game Theory-Based Decision-Making: In the final step, a non-cooperative game is executed among candidate CH nodes. Based on their energy status and individual utility, each node selects its optimal transmission strategy. This results in an intelligent and stable balancing of energy consumption within the cluster.

• Data Aggregation

To store the maximum amount of data during communication between nodes while using the least memory, received data is compressed before any storage or transmission. If $L(s_i)$ is the message length and $\frac{L(si)}{a}$ is the compressed message length, the energy saved is given by the following relation. In this relation, E_{comp} is the energy consumed for compression.

• Distance Calculation

The candidate must have the shortest distance among all other nodes in the target cluster. The distance between two points ppp and qqq is the length of the line segment ($\overline{pq}$) connecting them. In rectangular coordinates, if $P = (p_1, p_2, \dots, p_n)$ and $q = (q_1, q_2, \dots, q_n)$) are two points in Euclidean space, then the distance between them is calculated according to the following relation:

$$d(p,q) = \sqrt{(q_1 - p_1)^2 + (q_2 - p_2)^2 + \cdots + (q_n - p_n)^2} \tag{6}$$

• Calculating the Number of Neighbors

At the beginning of the cluster setup phase, each BTS sends a Hello message to its direct neighbors to gather the initial information needed for local analysis and entry into the decision-making game. This message includes the sender node's ID, its remaining energy level, its geographical coordinates, and the number of active neighbors within communication range. Given that BTSs in a GSM network are deployed within a specific geographical area and their locations are accessible via positioning systems, each node can locally calculate its Euclidean distance to its neighbors. After receiving Hello messages, each BTS analyzes the obtained information to determine its neighborhood structure and estimates node density, local interference patterns, and the energy status of its neighbors. This data is used in subsequent stages of the algorithm, particularly in selecting game strategies for CH election, evaluating cluster stability, and making decisions about operational status (active or low-power). Thus, the Hello message exchange process forms the foundation for establishing distributed clustering and the game-based mechanism aimed at enhancing energy efficiency and improving throughput in the GSM network.

• **Game Theory-Based Control**

The Profitable Energy Market Game (PEMG) method is used to control message transmission and reception. In the PEMG method, each candidate node for the CH role independently decides whether to participate in each execution round or to opt out. In this scenario, the market defines trading rules based on the player's approach. Here, the player has two possible actions:

1. Participate in the game.
2. Refrain from playing.

Each player calculates the payoff affecting other players or the payoff received from other nodes. The utility function is the value of the remaining energy. More precisely, the payoff depends on the player's strategy: if in sleep mode, the batteries are charged (energy is saved); or if they enter the game to send or receive messages. The PEMG method is executed separately within each cluster.

$$S_i(j),=\{1,2,\ldots N_i\} \tag{7}$$

where N_i is the number of nodes in each cluster per execution, $m_i(k)$ is the number of messages sent by $S_i(K)$, and $N_{Neighbours}$ is the number of neighbors of the *i-th* node. Also, $u(j)$ is the energy function used by the *i-th* node.

$$xi(j)=\begin{cases}1 & \text{Refrain} \quad \text{Participate game} \\ 0 & \qquad\qquad \text{from playing}\end{cases} \tag{8}$$

$$G_i=\{N_i, N_{Neighbours}, X_i(j)_{jENi}, U_i(j)_{jENi}\} \tag{9}$$

$$u_i(x_i(j))=\begin{cases}g_i(j)-C_i(j) & if \quad x_i(j)=o\exists x_i(k)=0 \\ 0\rightarrow if \quad x_i(j)=1 & \\ g_i(j)+f_i(j) & if \ x_i(j)=0\end{cases} \tag{10}$$

Here is the translation of the provided Persian academic text into natural, human-like English:

$C_i(j)$ is the total energy consumed by node i in cluster j, $g_i(j)$ is the utility function representing the remaining energy and $f_i(j)$is the energy harvested through battery charging.

When the *i-th* node decides to enter the game, it sends its messages while its local neighbors are not participating in the game. In this case, its utility function is given by Equation (10). When the node decides not to enter the game, it performs energy harvesting, and its utility function becomes $g_i(j)+f_i(j)$.

In the proposed method, each candidate CH node plays its own game individually and updates its strategy. To estimate the hybrid Nash Equilibrium (NE) strategy, the decision function or utility function of each player must be estimated. That is, $g_i(j)$ and its mathematical expectation E[u_i] must be estimated for each player. If the *j-th* node in the *j-th* cluster enters the market randomly with an entry probability of $P_i(j)$, then the mathematical expectation for node j is calculated using Equation (10).

$$\begin{aligned}E[U_i(x_i(J))]&=p_i(j)\times(g_i(j)+(1-p_i(j)) \\ &\times(g_i(j)+f_i(j))\times(1-\prod_{K\neq j}^{M_j}(1-p_i(k)))\end{aligned} \tag{11}$$

In this relationship, it is evident that when the sensor's battery is at its highest charge level, its chance of entering the game is at its maximum (i.e., $g_i(j)$—the remaining energy—is at its historical peak, and$C_i(j)=0$ meaning energy consumption is zero). To optimize the mathematical expectation for predicting participation or non-participation in the game, the derivative of the expectation is taken. By setting this derivative equal to zero in Equation (11), the maximum probability is obtained, since the derivative is taken with respect to $P_i(j)$ (j). Equation (12) gives the derivative, and Equation (13) corresponds to the maximum.

$$\frac{(C_i(j)+f_i(j))}{(g_i(j)+f_i(J))}\prod_{K\#j}^{M_j}(1-p_i(k)) \tag{12}$$

$$a_i(j)=\frac{C_i(j)+f_i(j)}{(g_i(j)+f_i(J)}$$

Then if defined:

$$g_i(k)=(1-P_i(k)) \tag{13}$$

Eaquation 14 can be concluded

$$\begin{cases} a_i(1)=q_i(2)\times q_i(3)\times\ldots\times q_i(M_i) \\ a_i(2)=q_i(1)\times q_i(3)\times\ldots\times q_i(M_i) \\ a_i(Mj-1)=q_i(1)\times\ldots\times q_i(M_j-2)\times q_i(M_j) \\ a_i(Mj)=q_i(1)\times\ldots q_i(Mj-2)\times q_i(M_j-1) \end{cases} \tag{14}$$

Equation (14) can be reconstructed and revised as Equation (15), because…

$$\left(\prod_{j=1}^{Mj}(q_i(k))\right)^{M_j-1}=\prod_{j=1}^{M_j}(a_i(j)) \tag{15}$$

Therefore, the optimal probability value and the optimal probability distribution function for each candidate CH node in the *j-th* cluster to enter the game will be given by Equation (16).

$$\left(\prod_{j=1}^{Mj}(1-P_i(k))\right)^{M_j-1}=\prod_{j=1}^{M_j}(a_i(j)) \tag{16}$$

The historical payoff function for nodes depends on their own strategy as well as the decisions of other neighboring nodes. The base utility matrix (payoff matrix) for the *j-th* node in the *j-th* cluster is shown in Table (2). To calculate the payoff matrix for each cluster in the game, a combination of decisions made by the nodes is formed, and then the matrix is constructed (whether a node enters the game or not).

Table (2): Historical Payoff Function for Nodes

	All$S_i(j)$ Participate game	*At least one candidate CH node enters the game.*
$S_i(j)$ *Participate game*	$g_i(j)-C_i(j)$	$g_i(j)-C_i(j)$
Refrain from playing $S_i(j)$	0	$g_i(j)+f_i(j)$

If we assume $=\{x_i(1),\ldots x_i(M_j)\}$ is the strategy vector of the candidate CH nodes, then the payoff matrix for $S_i(j)$ can be written as Equation (17).

$$U_i(j)\begin{bmatrix} I(g_i(j)-C_i(j)) & (g_i(j)-C_i(j)) \\ 0 & (g_i(j)+f_i(j)) \end{bmatrix} \tag{17}$$

In a symmetric game strategy, the entry strategy of the nodes and their decision to enter the game, as well as the decisions of their neighbors, are completely known. For example, all entries could be $X=\{1,\ldots,1\}$ (i.e., all enter), or when they decide not to enter the game, $X=\{0,\ldots,0\}$ (i.e., none enter). In reality, finding the best response for a candidate CH node to enter the game and make a decision is not feasible, and the condition for entering the game is the same for all nodes and their neighbors. Therefore, it is better for the game to be asymmetric and to solve an asymmetric Nash Equilibrium (NE) problem. In other words, the strategy M_j is mixed. That is, Table 2 transforms into Equations (18) and (19).

$$U_i(x_i(j)=0)=u_i(x_i(j)=1) \tag{18}$$

$$(g_i(j)-C_i(j)\times p=(g_i(j)+f_i(j))\times(1-(1-p)^{m_j-1}) \tag{19}$$

Therefore, based on Equation (19), P_E which is the probability of equilibrium (E)—for a problem with a mixed strategy is given by Equation (20).

$$P_{E_i}(j)=1-\left(1-\frac{(g_i(j)-C_i(j))}{(g_i(j)+f_i(j))}\right)^{\frac{1}{M_j-1}} \tag{20}$$

Since there exists a probability for P_E where $0<\frac{(g_i(j)-c_i(j)}{g_i(j)+f_i(j)}$, it follows that as the number of neighbors increases, the desired probability decreases (when the number of nodes grows, the likelihood of a node transmitting data is reduced). For example, in limited cases (M_j-1), the probability varies within a bounded range, and the probability of entering the game fluctuates between zero and one. Figure (2) illustrates the changes in a node's probability and payoff in the game as the number of neighbors in a cluster varies. As the number of nodes increases, the probability of entering the game decreases. Figure 3 shows the pseudocode for CH selection using the proposed method.

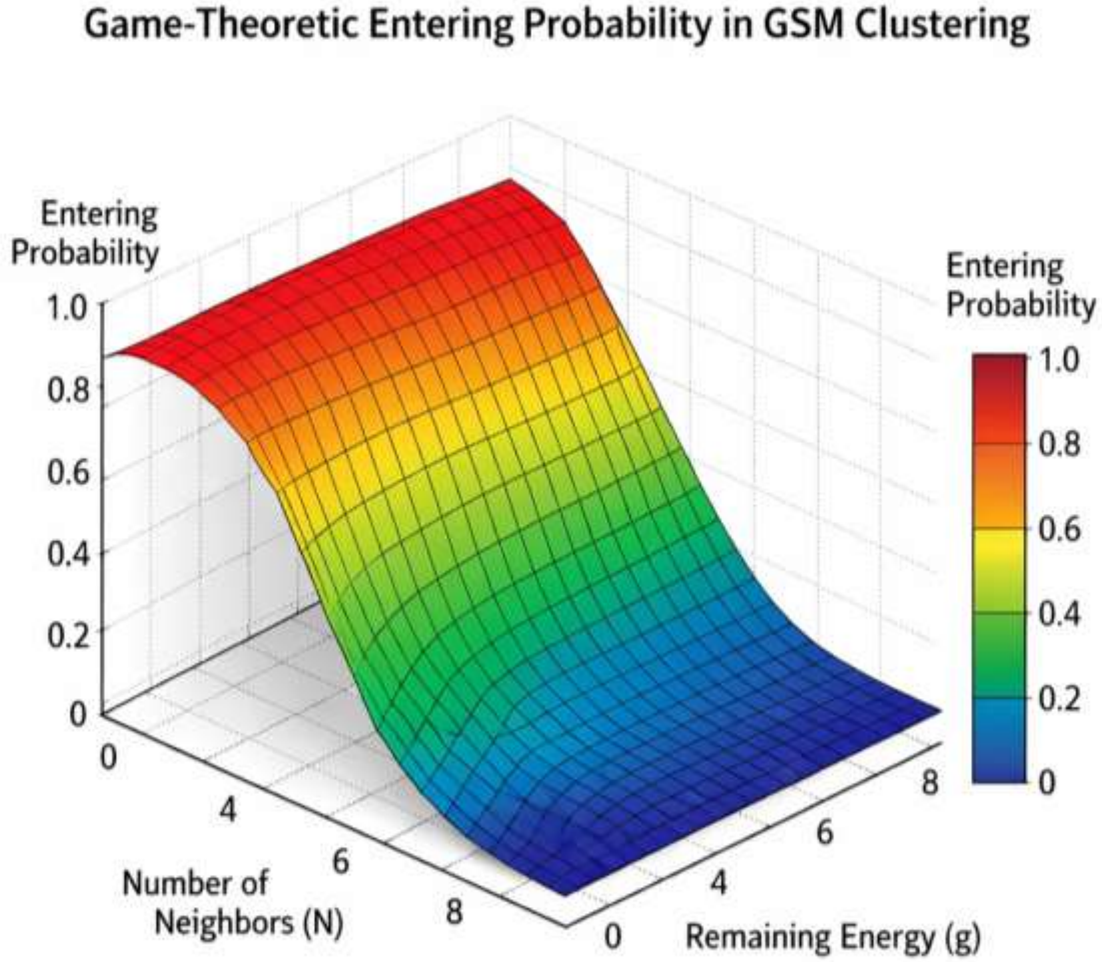

Figure (2): Variation in a node's probability and payoff in the game as the number of neighbors in a cluster changes.

Begin

Deploy N BTS nodes within the GSM coverage region
Initialize system parameters:
- Energy levels of BTSs
- BTS IDs and coordinates
- Neighbor list (initially empty)
- Transmission range, interference thresholds
- Base Station (MSC/BSC) location

For each time-slot (round):

1. Neighbor Discovery:

For each BTS:
- Broadcast Hello message containing:
  ID, residual energy, coordinates
- Receive Hello messages from neighbors
- Update neighbor list and compute Euclidean distance to each neighbor

EndFor

2. Virtual Cluster Formation:

- Each BTS groups itself with neighbors based on:
  • Physical proximity
  • Interference coupling
  • Load similarity (optional)
- Form virtual clusters in a fully distributed manner

3. Game-Theoretic CH Selection:

For each BTS inside a virtual cluster:
- Compute utility function U(i) using:
  • Residual Energy (E_i)

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        • Distance to BS/BSC (d_i)
        • Local Neighbor Density (ρ_i)
        • Interference Impact (I_i)
    - Share U(i) with neighbors
  EndFor
  - The BTS with maximum utility becomes the CH
  - Cluster members update their CH association accordingly
4. Operational Phase (Stable Phase):
  For each member BTS:
    - Report load/traffic state to CH
    - Follow CH instructions for:
        • Power control
        • Sleep/active switching
        • Local traffic forwarding
  EndFor
  - CH communicates aggregated control/traffic information
    to the BS/BSC based on network policies
5. Energy Update:
  For each BTS:
    - Deduct energy consumption based on:
        • Transmission power
        • Reception/processing load
        • Sleep/active state transitions
  EndFor
6. CH Re-evaluation:
  If CH residual energy < threshold OR
     cluster utility degraded:
    - Trigger CH re-selection in next time-slot
  EndIf

 EndFor
End
```

Figure (3) shows the pseudocode for CH selection using the proposed method.

4- RESULTS

To evaluate the performance of the proposed framework, a series of simulations were conducted in a GSM environment close to real-world conditions. In this evaluation, key metrics including cluster head energy consumption, cluster throughput, the stability of the cluster head selection process, and the probability of nodes entering the game were analyzed. In this study, the proposed game theory-based method was compared with several reference clustering algorithms and energy-aware models to determine the extent of improvement in energy efficiency, load distribution, and network stability. The goal of this section is to demonstrate how distributed decision-making and the non-cooperative game model can reduce interference, optimize energy consumption, and enhance clustering stability in GSM networks.

For this purpose, Table (3) presents the main configuration of the simulated network. In this scenario, the number of mobile users is considered to be between 200 and 2000, and the radio access structure includes one macro base station along with 12 micro cells. To create a realistic multi-layer environment, the coverage radius of micro cells is assumed to be between 100 and 300 meters, and the macro cell radius is set to 500 meters. The data generation rate per user is configured between 64 kbps and 1 Mbps, and the network is configured based on the GSM/EDGE standard in the 900 and 1800 MHz bands. Additionally, the total downlink capacity of the macro cell is considered to be approximately 20 Mbps, and the average data packet size is 1500 bytes.

Table (3): Details of the Simulated Network Settings

Parameter	***Value***
Number of Mobile Users (MSs)	200 – 2000
Number of GSM Microcells (BTSs)	12
Number of GSM Macro Base Stations	1
Microcell Coverage Radius	100 – 300 meters
Macrocell Coverage Radius	500 meters
Data Generation Rate per MS	64 kbps – 1 Mbps
GSM Standard	GSM/EDGE (900 / 1800 MHz)

Total Downlink Capacity (Macrocell)	≈ 20 Mbps (aggregate GSM/EDGE capacity)
Average Packet Payload	1500 bytes

In this research, a comprehensive set of performance metrics has been examined to accurately evaluate the proposed game theory-based clustering approach in GSM networks. The analysis criteria include base station energy consumption, network throughput based on effective data rate, Signal-to-Interference-plus-Noise Ratio (SINR), and the stability index of the clustering structure over time. To complete the evaluation and obtain a deeper analysis, two other critical metrics have also been measured: Spectral Efficiency, which indicates the effective utilization of frequency resources, and Network Lifetime, estimated based on the average number of active cluster heads during the simulation period. These six key metrics enable a fair and multi-dimensional comparison of the proposed approach with reference methods, providing a precise picture of the improvements in energy efficiency, network capacity, and cluster structure stability in real-world GSM environments.

Energy Consumption

Figure (4) presents a comprehensive comparison of energy consumption (in joules) among four clustering methods—GameTheory (the proposed method), LEACH, Kmeans, and Random—in the simulated GSM network environment. The results clearly show that the proposed GameTheory method achieves the most optimal performance in this key metric, with the lowest energy consumption of approximately 2.65 joules. This advantage stems directly from the inherent ability of the game theory-based approach to perform distributed resource optimization and strategic cluster head selection, which reduces communication overhead and enhances energy efficiency.

In contrast, the LEACH and Kmeans methods show higher energy consumption, at roughly 3.15 joules and 3.30 joules, respectively. The increased consumption in LEACH is largely due to its incomplete optimization in cluster head selection and load distribution. Meanwhile, Kmeans consumes more energy because of its centralized nature, requiring frequent communication with a central base station for clustering. The Random method, with an energy consumption of about 2.9 joules, performs between the proposed method and the classic LEACH and Kmeans approaches, reflecting its lack of a defined optimization mechanism. These results clearly demonstrate the effectiveness of the GameTheory method in significantly reducing energy consumption in GSM networks—a critical factor for extending network lifetime and ensuring operational stability.

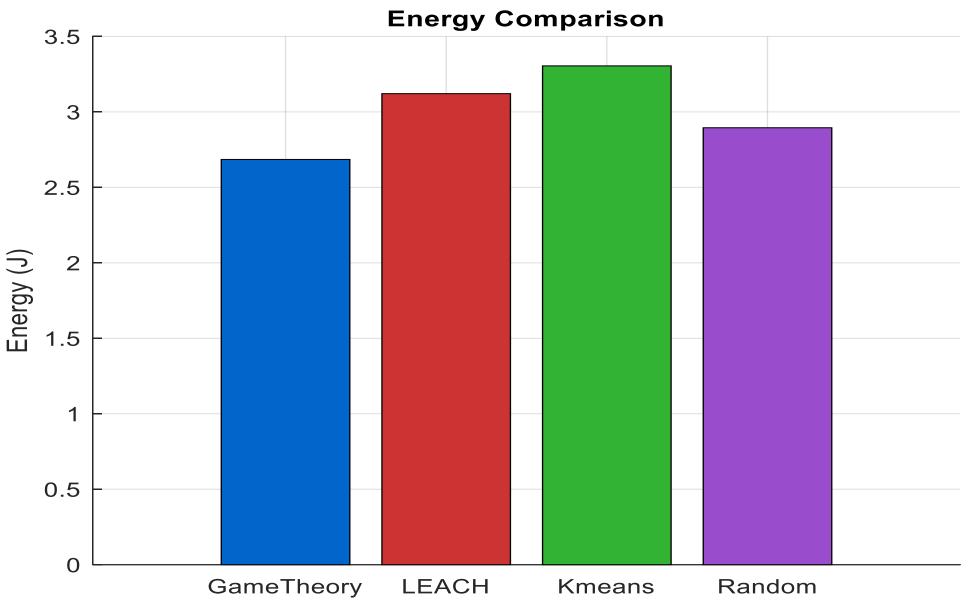

Figure (4) compares the energy consumption (in joules) of the GameTheory, LEACH, Kmeans, and Random methods in a GSM network.

Throughput

Figure (5) shows a comparison of network throughput for the four clustering methods—GameTheory, LEACH, Kmeans, and Random—in the GSM environment. As can be seen, the GameTheory method delivers the highest throughput, performing slightly better than LEACH. This indicates that the proposed approach, by leveraging game theory-based decision-making, has managed to reduce interference, optimize radio resource allocation, and create more stable communication paths.

The Kmeans method shows lower throughput compared to the first two methods, which is due to its fixed clustering structure and lack of dynamic adaptation to real-time network conditions. The Random method records

the lowest throughput, as it lacks any effective mechanism for efficient cluster head selection and communication load management.
These results demonstrate that the strategic selection of cluster heads and optimal power adjustment play a crucial role in improving data transmission capacity and efficiency in GSM networks.

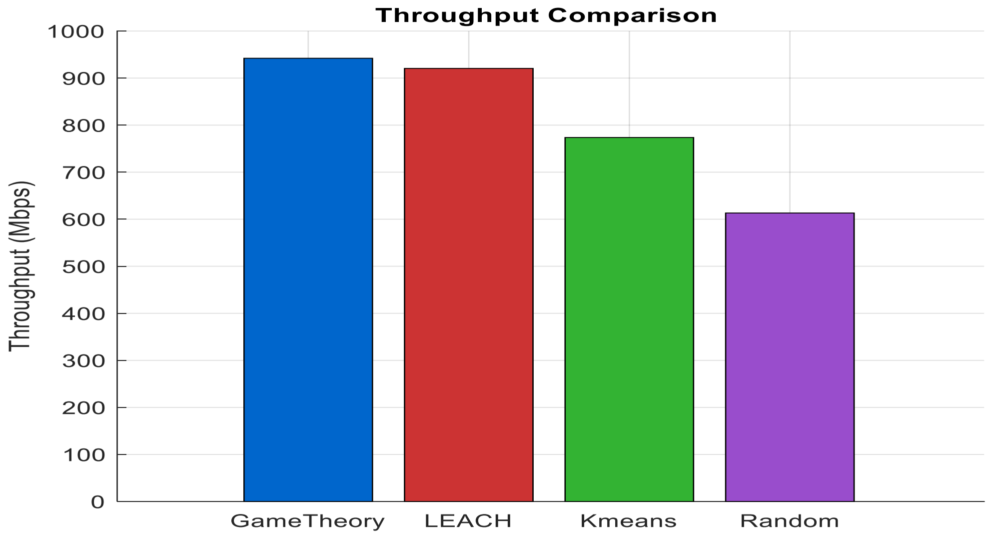

Figure (5) Comparison of network throughput for the four clustering methods in a GSM environment

• SINR Value

Figure (6) presents a comparison of the SINR value for the four clustering methods—GameTheory, LEACH, Kmeans, and Random—in the GSM network. As can be seen, the GameTheory method achieves the highest SINR value, demonstrating its ability to reduce interference and maintain higher signal quality in communication paths. Following that, the LEACH method performs relatively well, but due to its non-analytical cluster head selection, it experiences a higher level of interference compared to the proposed approach.
The SINR value for the Kmeans method is noticeably lower, which stems from its static clustering structure and its inability to adapt to changes in the interference environment. The lowest value belongs to the Random method, which, due to the absence of any optimization criteria in the clustering process, records the highest level of interference and the lowest signal quality.
These results indicate that the proposed game theory-based approach has been able to significantly improve signal quality through better power management and clustering structure.

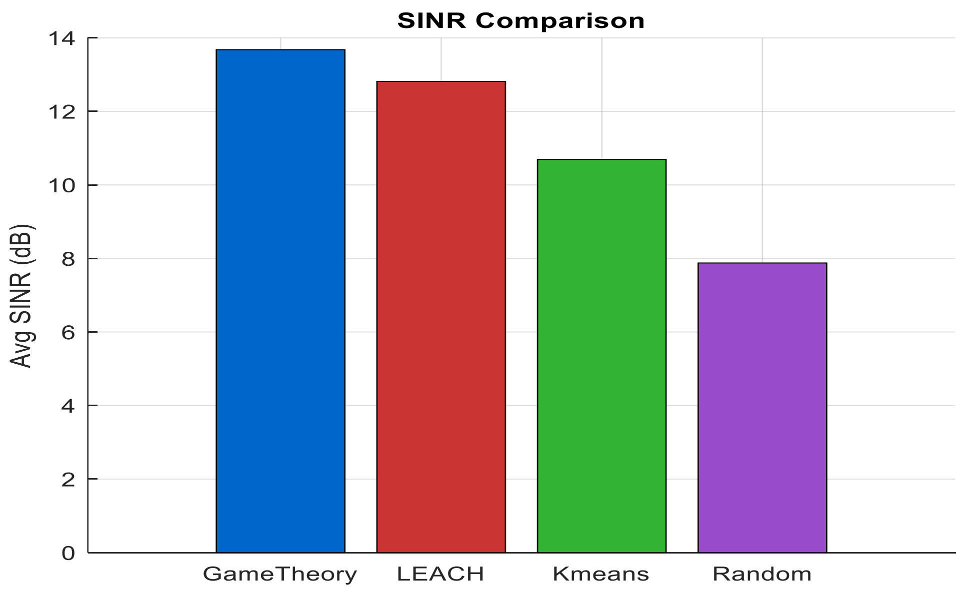

Figure (6) Comparison of the SINR value among the four clustering methods—GameTheory, LEACH, Kmeans, and Random—in a GSM network

• Cluster Head Stability

Figure (7) compares the stability of cluster heads for the four methods: GameTheory, LEACH, Kmeans, and Random. The results show that the GameTheory method provides the highest level of stability. This means that cluster heads in this approach last longer and require fewer frequent changes—a factor that ultimately reduces network control overhead and improves coordination among nodes.

The LEACH method also shows acceptable performance but exhibits more fluctuations compared to the proposed method. This is because its cluster head selection is periodic and does not account for energy dynamics and node positions. In the Kmeans method, due to its fixed clustering structure, adaptability is limited, which leads to reduced cluster head stability. The lowest level of stability belongs to the Random method, as its selection without clear criteria results in unnecessary changes and severe instability in the cluster structure.

This comparison indicates that using intelligent, game theory-based decision-making can play a crucial role in maintaining the stability and efficiency of the clustering structure.

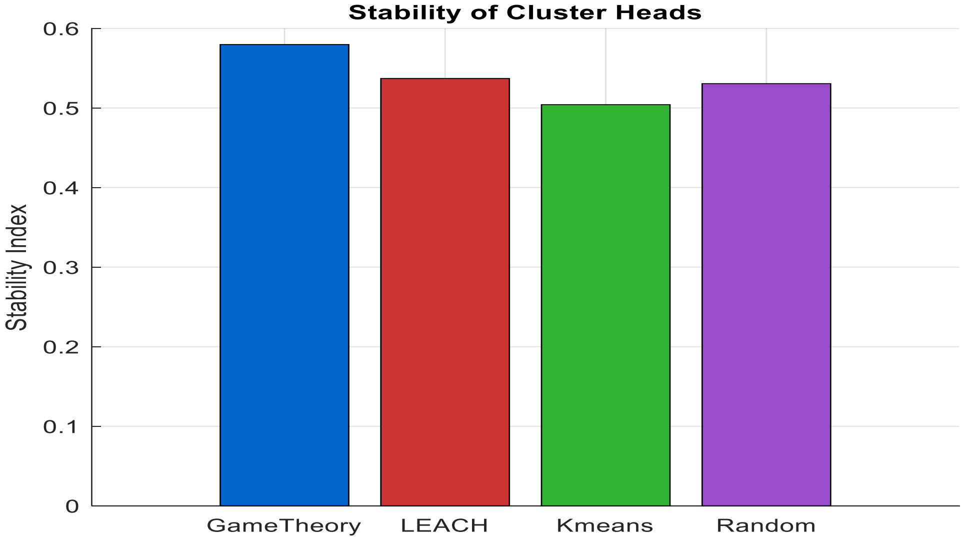

Figure (7) Comparison of cluster head stability among the four clustering methods in a GSM network

• Spectral Efficiency Comparison

Figure (8) presents a comparison of spectral efficiency. The results show that the GameTheory method achieves the highest spectral efficiency, indicating a more effective utilization of bandwidth and a reduction in wasted radio resources. This advantage stems from the dynamic and coordinated decision-making policies within its clustering process, which enable intelligent channel allocation and reduce interference between nodes.

While the LEACH method performs adequately, it demonstrates lower efficiency compared to the proposed method. This is because its cluster head selection structure does not guarantee real-time resource optimization. The Kmeans method also exhibits lower spectral efficiency due to its fixed clustering and inability to adapt to the changing conditions of the radio environment.

The lowest spectral efficiency belongs to the Random method. Due to its lack of a defined control structure, it leads to inefficient channel use and increased interference.

These results emphasize that the game theory-based approach can significantly improve the network's spectral efficiency.

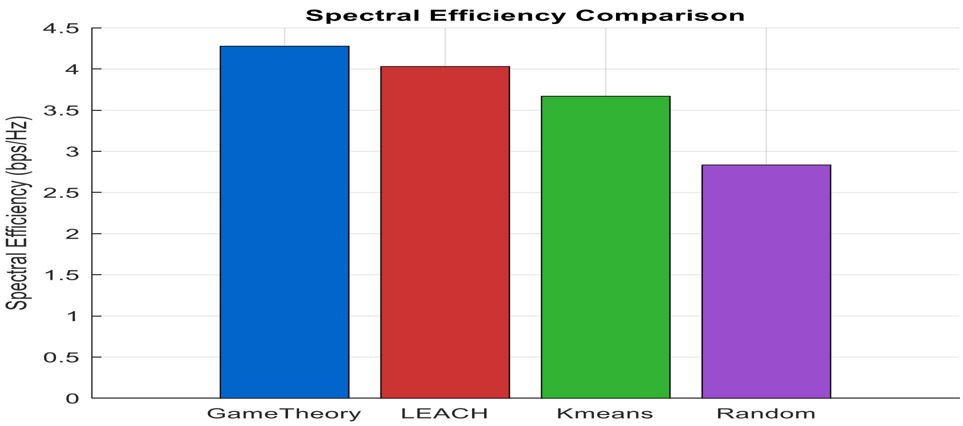

Figure (8) Comparison of spectral efficiency for the four clustering methods in a GSM network

• **Network Lifetime**
Figure (9) compares the network lifetime for the four methods. As the results show, the proposed method provides the longest network lifetime, demonstrating that this approach has managed to balance energy consumption distribution among nodes more effectively. This balance helps nodes deplete their energy later, allowing the network to remain operational for a longer period. The LEACH method also performs reasonably well, but its network lifetime is slightly shorter than the proposed method. This is due to its periodic cluster head selection and insufficient attention to the real-time energy status of nodes. The Kmeans method has a more limited lifetime because of its fixed clustering structure and lack of an energy optimization mechanism. Finally, the Random method shows the shortest network lifetime. Since energy consumption is distributed among nodes without any control criteria, some nodes fail much earlier than others. This comparison indicates that using the intelligent decision-making based on the proposed game theory can have a significant impact on enhancing network longevity.

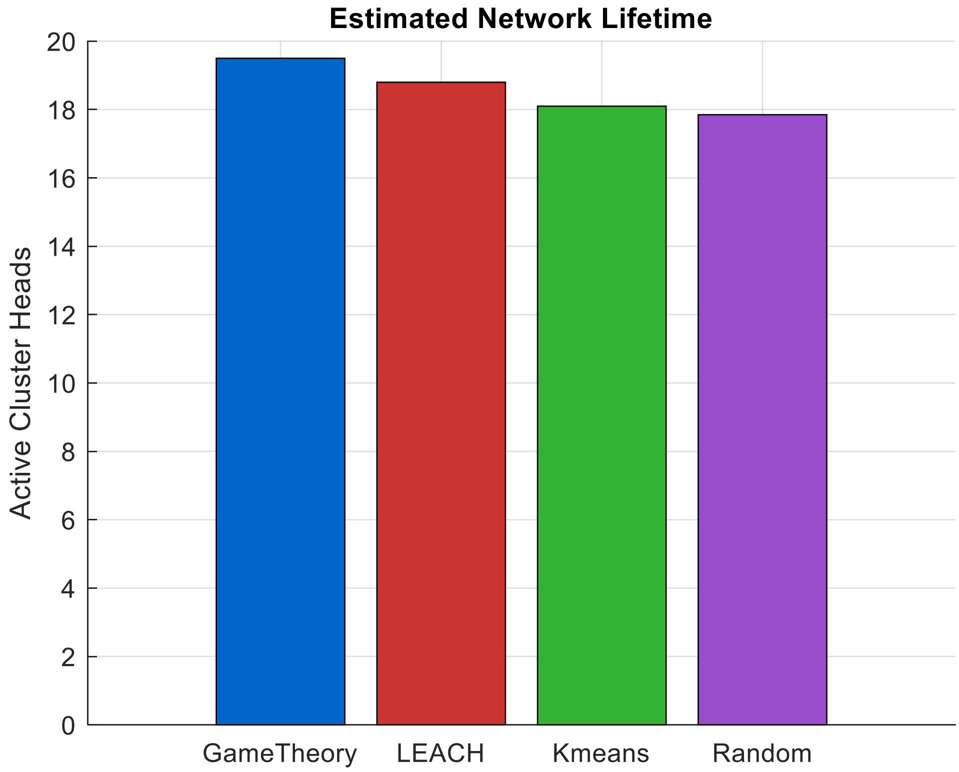

Figure (9) Comparison of network lifetime for the four different clustering methods in a GSM environmen

DISCUSSION
This study conducted a comprehensive analysis of key performance indicators to evaluate four clustering approaches—GameTheory, LEACH, Kmeans, and Random—in a GSM-based network environment. The findings provide a clear picture of the structural strengths and weaknesses of each method. Table 4 summarizes these results qualitatively.
The GameTheory method demonstrated superior and stable performance across most metrics. The combination of rational decision-making mechanisms, repeated interactions among nodes, and adaptability to real-time network conditions resulted in balanced energy distribution, reduced interference, a stable cluster structure, and enhanced node cooperation. These characteristics significantly improved its performance in metrics such as spectral efficiency, average SINR, cluster stability, packet delivery rate, and, notably, network lifetime.
In contrast, while the LEACH method benefits from a simple design and periodic cluster head selection, its performance fluctuates in certain phases due to insufficient consideration of residual energy and environmental parameters. Consequently, it cannot guarantee long-term resource optimization.
The Kmeans method, based on spatial clustering, creates orderly structures. However, due to its static nature and inability to respond dynamically to changes in traffic load and node energy levels, it underperforms compared to the proposed method in metrics like energy consumption and cluster stability.
The Random method, serving as a simple baseline with no cluster head selection logic, exhibited the lowest quality levels across all metrics. Its results naturally reflect the effects of unmanaged resources and uncoordinated energy consumption.

Overall, these analyses emphasize that employing a game theory framework provides a structured and adaptive approach to solving the clustering problem in GSM networks. By simultaneously improving several key metrics, it can serve as an effective solution for enhancing the efficiency and stability of future-generation networks.

Table (4) Qualitative comparison of the four clustering methods in a GSM network

Evaluation Metric	GameTheory	LEACH	Kmeans	Random
Energy Consumption	Very low; balanced energy distribution through cooperative decision-making	Moderate; fluctuating consumption due to periodic CH rotation	Relatively high; static clustering leads to uneven load	Very high; no control over energy distribution
Cluster Stability	Very high; stable and adaptive cluster structure	Moderate; dependent on CH rotation cycles	Low; sensitive to spatial changes	Very low; highly irregular structure
Spectral Efficiency	Very high; intelligent channel allocation and interference reduction	High; lacks instant optimization	Moderate; geometry-based	Low; strong interference
Average SINR	High; cooperative interference management	Medium-high	Medium	Low
Packet Delivery Ratio (PDR)	High; stable link management	Moderate	Medium-low	Low
Network Lifetime	Very long; optimized CH selection and energy load balancing	Long; limited long-term stability	Medium	Very short
Adaptability to Dynamic Conditions	Very high; responsive to real-time changes	Medium	Low; static clustering	Very low
Computational Complexity	Medium; requires game-based analysis	Very low	Medium	Very low
Practical Applicability	Very high; suitable for dense and dynamic networks	Medium	Limited to static scenarios	Very low

5- CONCLUSION

This study conducted a comprehensive evaluation of four clustering methods—Game Theory Based Clustering, LEACH, the K-Means algorithm, and Random clustering—in GSM communication networks. The analysis was based on performance indicators such as energy consumption, spectral efficiency, signal-to-interference-plus-noise ratio (SINR),cluster stability, network lifetime, and throughput. The results consistently demonstrated that the game theory-based method outperforms conventional approaches in nearly all metrics.

The superiority of the game theory model stems from its rational decision-making structure, which allows nodes to dynamically adjust their clustering strategy based on payoff function optimization. This approach leads to balanced cluster head (CH) selection, reduced intra-cluster interference, and optimal distribution of communication load among nodes. Consequently, energy consumption is significantly reduced, and network lifetime shows a marked increase compared to LEACH and K-Means methods. In contrast, the Random method, due to its lack of an optimization structure, exhibits the weakest performance across all indicators, highlighting the need for intelligent clustering in large-scale GSM networks.

From a communication quality perspective, game theory-based clustering, by forming adaptive and stable clusters, leads to a substantial improvement in SINR and spectral efficiency. This improvement directly translates into higher packet delivery ratios and overall throughput, indicating a stable and reliable communication structure. LEACH shows moderate performance in these metrics, while K-Means faces limitations under dynamic or heterogeneous spatial distributions. Simulation results revealed that static geometric clustering alone is insufficient for real-world GSM network conditions, as variations in traffic load and user mobility play a crucial role in network dynamics.

Overall, the findings of this research indicate that the game theory-based clustering method is an efficient, scalable, and suitable solution for GSM networks, particularly in dense and dynamic environments. Its significant advantage across various performance metrics makes it a powerful candidate for future-generation cellular systems. For future research, it is recommended to explore the use of machine learning models for extracting adaptive payoff functions, mobility-based predictive models, and implementation in 5G and Beyond 5G networks to further enhance the method's efficiency.

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