# Dynamic Optimization-based Clustering in Hexagonal Topology for Enhancing Network Lifetime of WSNs

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***ABSTRACT***

*Distribution of Internet-of-Things sensors in wireless sensor networks (WSNs) often leads to transmission conflicts and inefficiency of energy utilization, resulting in decreased sensor communication and incomplete data for decision making. Utilizing hexagonal topology and its properties such as one distance-to-neighbor, one distance-to-cluster, and three-axis coordinates can be exploited for energy efficient optimization. Leveraging a network optimization model created in AMPL with network simulation created in Contiki-NG Cooja, this research demonstrates that WSNs with hexagonal network topology can benefit from clustering which improves network lifetime, and therefore, enhances WSNs reliability by reducing total network energy consumption. Additionally, dynamic clustering further improves network lifetime for the WSN where the cluster-member hopping energy cost and cluster-head transmission energy cost ratio is 33.5% or less.*

***KEYWORDS***

*Wireless Sensor Network, Hexagonal topology, Cluster, Optimization, Network lifetime*

## 1. Introduction

Wireless Sensor Networks (WSNs) are core enablers of the Internet of Things (IoT), supporting sectors such as space, transportation, manufacturing, military systems, and modern applications including habitat monitoring, precision agriculture, healthcare [20], and natural-disaster detection. They collect large-scale physical data essential for monitoring, tracking, and decision-making.

Improving WSN reliability has been a major research focus. In real deployments, sensor distribution often creates transmission conflicts and inefficient energy use [1], leading to reduced communication and incomplete datasets [2]. Even small data-loss rates, 5% or 20%, can degrade recognition sensor performance to 45% and 84%, respectively, making the data unreliable [38].

The network's ability to reliably deliver data, depends on the network topology and parameters, and on the transmission properties of the device and of the medium [7]. While WSN reliability is multifaceted depending on the specific application and requirements, in a broad sense WSN reliability is characterized and assessed by sensing coverage, network connectivity, energy

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efficiency and data handling capacity [11],[12],[42].

Theoretical analysis shows that when using a fixed quantity of sensor nodes, a hexagonal topology can attain maximal coverage [3]. Njoya et al. [17] in their study of WSNs employed the hexagonal lattice to demonstrate a power-saving network design. In a recent study by Li et al. [2] they employed the Fruchterman–Reingold Hexagon algorithm modified for WSN deployment to take full advantage of sensors' hardware capabilities. Similarly, dynamic clustering is a groundbreaking method for designing energy efficient sensor network to achieve reliable data transmission and scalability. While clustering protocols such as LEACH [23], HEED [24], BSC [26], JCR [4], DCPVP [25] and others offer innovative solutions for load balancing which improves network reliability; they do not impose upon unique features of the network's physical layer topology. With the advancement of routing protocols such as Routing Protocol for Low-Power and Lossy Network (RPL), the objective functions assignment to sensor nodes can now be dynamic, supporting multiple clustering patterns, and therefore, more energy efficient when it comes to the energy cost of clustering [32], [33], [34].

Nevertheless, the mechanisms through which hexagonal topology may optimize network lifetime are still largely unexplored. Moreover, it's not clear whether and how, leveraging hexagonal topology properties such as one-distance-to-neighbor, one distance-to-cluster and three axis coordinates, the packet transmission can be achieved with improved energy efficiency. In addition, the previous methods for dynamic clustering [23], [24], [25] did not lend themselves to an analysis of the hexagonal topology's impact on the total network energy consumption and packet handling capacity.

Thus, the aim of this paper is to develop an optimization model showing that the Routing Protocol for Low-Power and Lossy Network (RPL) protocol performs better with use of static and dynamic clustering in hexagonal grid topology for large-scale WSNs deployments, in order to enhance wireless sensors network (WSN) reliability. Specifically, the study shows that the use of the optimization algorithm improves networks' energy efficiency. With leveraging unique hexagonal topology properties, this is achieved via optimization objective to maximize network's lifetime by selecting the most energy efficient cluster pattern for each time interval.

There are several contributions this study makes. It is the first study to systematically analyze and demonstrate the combined value of three fundamental hexagonal-grid properties: (i) one-distance-to-neighbor, (ii) one-distance-to-cluster, and (iii) three-axis coordinate symmetry. While existing research overwhelmingly concentrates on the one-distance-to-neighbor feature, primarily because it simplifies optimization, this work expands the scope of hexagonal topology analysis in a novel and meaningful way. Secondly, by leveraging one distance-to-cluster, this research contributes for the first time to a better understanding of the ways that the cluster heads can be identified and the new WSNs can be deployed, as well as, the existing WSN can be enhanced for higher reliability and longer lifetime. Furthermore, the three axis coordinates provide symmetry and ease of traversing all of the node neighbors, used for dynamically allocating cluster members and generating cluster patterns. Finally, this work opens promising directions for future research, particularly the integration of Deep Reinforcement Learning to refine cluster sizing and matching. Such approaches could enable WSNs to learn from historical data, automate decision processes, and significantly elevate overall network quality.

## 2. Overview & Discussion of Literature

Although the origins of WSNs extend back several decades in military and industrial contexts [22], recent advances in computing, along with their integration into IoT and Big Data ecosystems, now enable large-scale data collection and analysis [6]. The following sections of the literature review (outlined in Figure 1) examine reliability, hexagonal topology, and clustering in WSNs, and highlight the gap in existing research that motivates this study.

With sensors not only collecting data but also being interconnected with the broader internet, modern WSNs have become more intelligent, leading to larger scale deployments and broader versatility of applications [21]. As a result, in recent years, there has been extensive research on WSNs reliability in terms of topics such as sensing coverage [1], [2], [8], [7], [11] and network connectivity [1], [11], [14], [15], as well as data handling capacity [7], [42], and overall network's energy efficiency [8], [12]. However, most of the reliability research mentioned above has been studied using the WSNs with flat communication topology. WSN flat topology is when, from a communication perspective, all nodes are equal and routing is defined on demand, while hierarchical topology is where there is a child-parent relationship between the nodes, and communication hierarchy is defined before any communication takes place [19]. This hierarchical topology enables the use of clustering which has been researched in recent years in terms of network connectivity, sensing coverage, energy efficiency and data handling capacity.

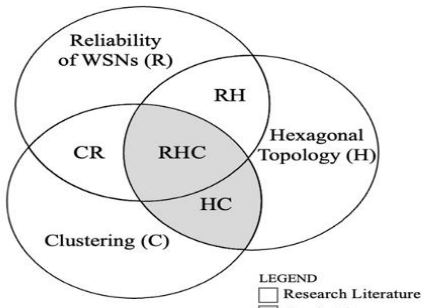


Figure 1. Literature Review Diagram

From the physical network layer perspective, the WSNs can have ring, star, tree, grid/mesh or fully-connected mesh topology [21]. Within grid topology deployments, patterns typically used are random, triangular, square and hexagonal lattice [15]. Grid-based location information can be used against insider treats in WSNs [5]. Hexagons have only one distance between a hexagon center-point and its neighbors', unlike the two distances for a square, and three distances for triangular lattices. This one distance-to-neighbor property greatly simplifies performing analysis, running optimization and smoothing over gradients [13]. Additionally, theoretical evidence demonstrates that a hexagonal topology achieves maximum coverage using a set number of sensor nodes [3]. The central focus of Tang's work [3] was to show via simulation studies, how the topology resulting from the virtual-force algorithm based on physical laws in a dusty plasma system {VFA-DP) is much closer to a hexagon, compared to the previous VFA-LJ (virtual-force algorithm based on the Lennard-Jones potential) algorithm. Consequently, the goal in deploying mobile sensor networks is to establish a hexagonal network topology with minimal energy consumption [3]. In order to further understand the effects of hexagonal topology, Li et al. [2] employed the Fruchterman–Reingold Hexagon algorithm modified for WSN deployment to take full advantage of sensors' hardware capabilities. And according to Njoya et al. [17] employing the hexagonal lattice enables a power-saving network design.

Clustering in WSNs is when sensor nodes are grouped into clusters based on predefined criteria such as proximity, energy levels, or communication cost. It exploits a hierarchical communication topology, where node within each cluster is elected as the cluster head (CH) and the remaining nodes within a cluster are cluster members (CM). Dynamic clustering refers to the dynamic nature of a network where clusters are not static. Instead, they are dynamically formed and reconfigured based on a predefined set of criteria such as energy consumption of CHs as was first proposed in Low Energy Adaptive Clustering Hierarchy (LEACH) protocol [23], [25]. Some clustering protocols maximize the network's lifetime through the good characteristics of stochastic fractal search optimization [9]. Dynamic clustering is a pivotal concept that significantly enhances the reliability and scalability of WSNs. By reducing the number of transmissions and utilizing data aggregation, dynamic clustering significantly conserves energy, which is a critical concern in WSNs due to the limited battery life of sensor nodes [19]. Since the foundation of network topology is based on CHs, the selection of CHs is one of the essential problems in dynamic clustering. Hybrid Energy Efficient Distributed (HEED) clustering protocol [24], [25] takes into account residual energy and communication cost for selection of CHs, and improves the CHs distribution in comparison with LEACH. Noting the substantial overhead during iterations in HEED, the Backoff Strategy Clustering (BSC) protocol [26], [28] implements a random backoff timer to manage the selection of CHs. In this protocol, nodes with shorter back-off times are more likely to become CHs. BSC effectively produces a well-distributed set of CHs while significantly reducing the overhead involved in their selection. The distributed clustering protocol based on voting and priority (DCPVP) decreases the cluster construction time and consequently energy consumption, which improves the lifetime of the network [25]. Hybrid Snake Whale Optimization (HSWO) algorithm selects the most optimal cluster head from the clusters by eliminating the worst ones with the consideration of constraints such as delay, energy, and distance [27], while using decision-making algorithm Dempster-Shafer Theory (DST) for trusted clustering with the Whale Optimization Algorithm (WOA) for routing, integrates trust management into routing protocols for trust-aware clustering [18]. Meanwhile, Hoang et al. [37] use harmony search algorithm (HSA) to select the CHs via centralized optimization, and Improved Q learning based Artificial Bee Colony (IQ-ABC) algorithm can be used for the same purpose [43], while the Termite Queen Optimization algorithm (TQOA) is used for determining optimal number of CHs [41]. Animi et al. [29], Tian et al. [30] and Lin and Üster [31] discuss cluster size optimization and efficient data forwarding in WSNs, while Yadawad and Joshi [10] propose reliable routing and minimal delay of packet transmission by employing Weighted Practical Byzantine Fault Tolerance (WPBFT) algorithm. However, when it comes to clustering in WSNs, the hexagonal network topology is not considered, nor is the newer Routing Protocol for Low-Power and Lossy Network (RPL). RPL's Minimum Rank with Hysteresis Objective Function (MRHOF) aims to select stable, high-quality links to reduce overall network traffic in order to improve reliability, and it uses hysteresis to prevent frequent changes in CH (parent) selection, enhancing network stability [39]. Optimization objective is to minimize the intra-cluster communication cost and optimize the energy distribution of the network. Regardless of using the distributed or search algorithms, this load balancing improves network reliability by distributing the energy consumption among various nodes via rotating the role of the cluster head among cluster members, ensuring that no single node bears the brunt of energy depletion.

As mentioned previously, only two studies to date investigated WSNs reliability in hexagonal topology in terms of network sensing coverage [2] and network lifetime when deployed in a circular coverage region [17]. No studies that examine the relationship between dynamic clustering and hexagonal topology could be found. In addition, none of the previously mentioned studies attempted to explore how dynamic clustering in hexagonal topology affects energy efficiency of the network. Therefore, to the best of our knowledge, there has been no research into how static clustering and dynamic clustering in hexagonal topology of WSNs might affect its performance, and whether this might lead to improved energy efficiency. While studies on dynamic clustering in other topologies have been conducted as reviewed above, the topic of dynamic clustering in hexagonal topology is a notable omission from the current canon of research into WSNs performance, especially given that the hexagonal lattice achieves maximum coverage using a set number of sensor nodes [3]. In order to address this issue, this study aims to investigate how static and dynamic clustering in hexagonal topology improves energy efficiency of WSNs.

# 3. PROPOSED APPROACH & METHODOLOGY

The proposed methodology approach provides a description of the Motivation for Hexagon Topology (Section 3.1), Network Model (Section 3.2), Optimization Model (Section 3.3), Network Simulation (Section 3.4), and is concluded by the Evaluation Approach (Section 3.5).
The overall approach, as shown in Figure 2, starts with calculating maximum cluster size N based on the hopping energy and transmission energy for a hexagonal network size n (see Section 3.2.3). Using the one distance-to-cluster property (see Section 3.1.2), all viable clustering patterns are generated up to the cluster size N, for the given hexagonal network size n. Once all clustering patterns are generated, network simulation is constructed to compute the Network Lifetime with clusters and without clusters (see Section 3.4 and Section 3.5.1). Network simulation is also used to simulate the data sensing activity for use in the optimization model. Optimization model objective is to maximize network lifetime and is designed to select the best clustering pattern for every data-sensing time interval until sensor nodes are depleted (see Section 3.3.1 and Section 3.3.2). The optimization model aims to confirm the simulation results in terms of network energy efficiency (see Section 3.3 and Section 3.5.2) and demonstrate the effectiveness of the dynamic clustering in hexagonal topology (see Section 3.5.3).

All of the above components are discussed in the following subsections.

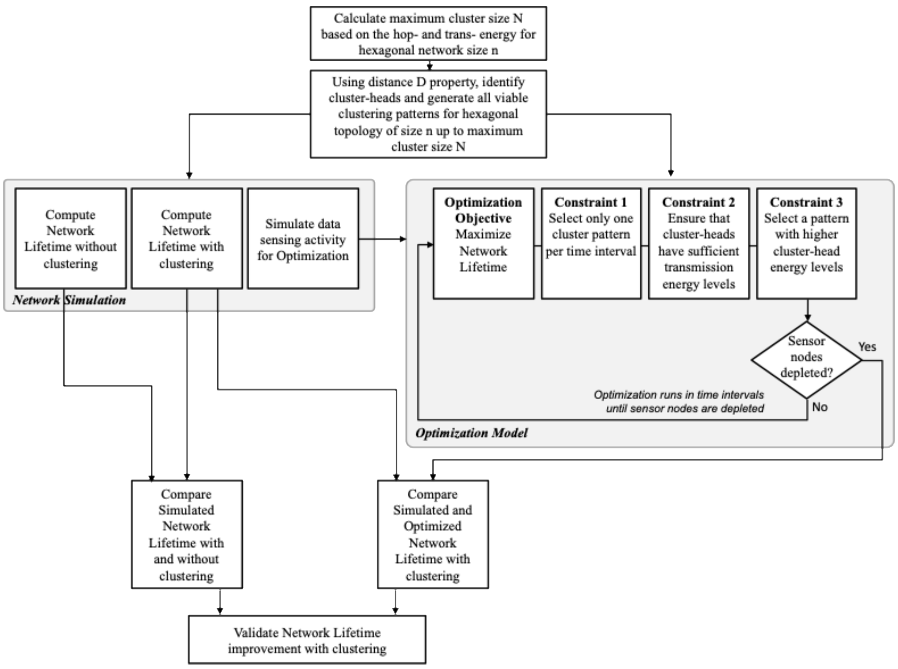


Figure 2. Methodology approach flowchart

## 3.1. Motivation for Hexagonal Topology

While hexagonal lattice has been extensively used in telecommunications, medical imaging, gaming, transportation and other industries, it has been largely omitted in large-scale WSNs implementations. For example, rideshare companies like Uber and DiDi, use hexagonal grid to assign drivers to riders (and deliveries) [13-14]. Uber's platform combines the benefits of a hexagonal global grid system with a hierarchical indexing system to optimally match drivers to riders. This is accomplished by pairing riders and drivers in a batch optimization, aiming to minimize everyone's wait time [13-14]. This efficient optimization is mainly possible because of utilization of the hexagonal lattice and its unique properties.

This body of work aims to leverage these unique hexagonal grid properties for dynamic optimization-based clustering in order to enhance network lifetime of wireless sensor networks.

#### 3.1.1. One distance-to-neighbor property

In addition to regular and complete tessellation, the hexagon lattice has a unique distance property, such that the distance between two adjacent hexagons is always the same [15]. Unlike the triangular lattice that has three distances to its neighbors and the square lattice that has two distances to its neighbors, the hexagonal lattice has only one distance to its neighbors as shown in Figure 3 [15]. This is an extremely useful property for network optimization as it is possible to efficiently account for the number of hops and transmissions within the hexagonal network of sensors. One distance-to-neighbor property (d) greatly simplifies performing analysis and smoothing over gradients [13].

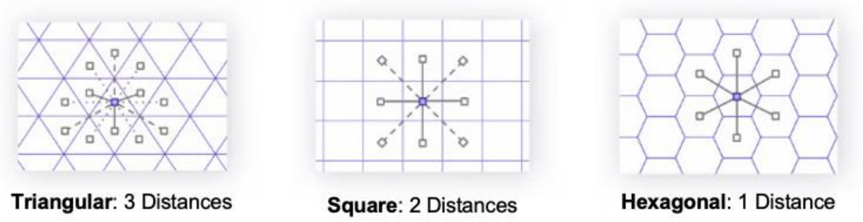


Figure 3. Distances to its neighbors [15]

#### 3.1.2. One distance-to-cluster property

For clustering in hexagonal topology, to have a uniform distance *D* for all cells in the network, including the cluster heads, cluster size *N* must obey the following relation [35]:

$$N(a, b) = a^2 + ab + b^2, a \geq 0, b \geq 0$$

In the above equation $a$ and $b$ are the number of cells between adjacent cluster centers on a 60-degree grid described in more detail in Section 3.1.3. For example, see Figure 4 for cluster size N(a, b) = N(2, 3) = 19. Consequently, the distance *D* can be calculated using only the cluster size *N* and the radius *R* of the cell itself using the following equation:

$$D = R * \sqrt{3 * N}$$

The above equation is useful for optimization modeling. For the purposes of dynamic clustering with one base station in the center of the network region, only the patterns with one of the cluster head's centers being in a network center are considered. Those cluster sizes are **N**(a, b) = **7**(2, 1), **19**(3, 2), **37**(4, 3), **61**(5, 4), **91**(6, 5), and so on.

In the event of the wireless sensor network having multiple base stations, the same cluster size principle applies. In this case, network topology with multiple base stations would be treated as tessellation of multiple WSNs with single base station. For example, wireless sensor network with seven (7) base stations, would consider seven (7) distinct WSNs depicted in Figure 4 that are tiled into a large hexagon.

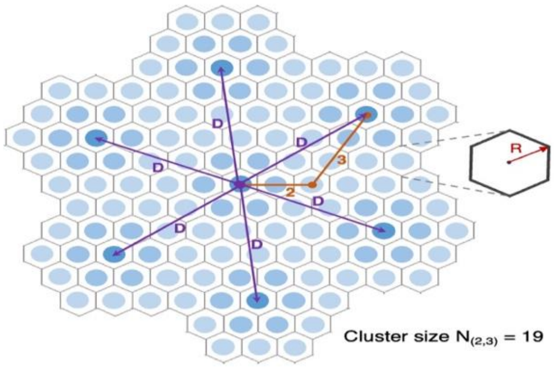


Figure 4. Clusters uniform distance property

### 3.1.3. Three 60-degree axis property

One of the main benefits of the square lattice is the ability to easily identify location of all nodes and their neighbors using the (x, y) coordinates, while effectively navigating the square grid. The hexagonal lattice behaves similarly, leveraging three (3) 60-degree axis. The three coordinates (p, q, r) effectively identify each node's location and help navigate the hexagonal grid, as depicted in Figure 5. Furthermore, the sum of the three coordinates (p, q, r) is always zero.

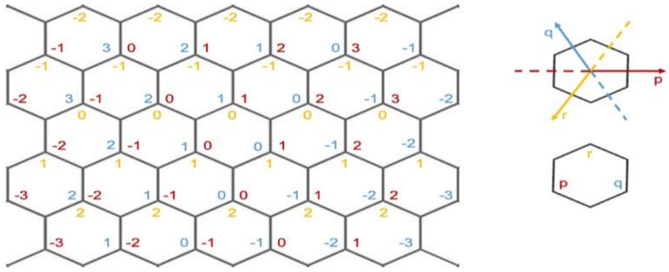

Figure 5. Three axis and coordinates of hexagonal grid

The three 60-degree axis property along with its (p, q, r) coordinates, provides symmetry and ease of traversing all of the node neighbors, used for efficiently allocating cluster members dynamically and generating cluster patterns.

## 3.2. Network Model

Consider a WSN with homogenous nodes deployed in hexagonal, hierarchical mesh topology with a single base station (also known as a sink node) placed in the center. Broadly speaking, the homogeneous nodes have the same capability of sensing, processing and packet forwarding. When placed in the hierarchical topology, the different roles are assigned to the nodes, and communication takes place in a hierarchical manner. The hierarchical topology enables formation of clusters, where cluster members communicate with cluster heads, and cluster heads communicate directly with the base station (see Figure 6).

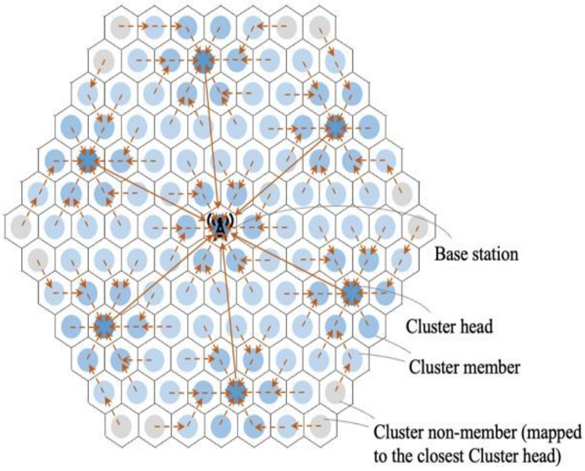


Figure 6. Network topology with clusters

### 3.2.1. Model Assumptions

The sensor nodes are deployed in a circular region surrounding the base station (see Figure 6). All nodes assume a short-range multi-hop communication in all six directions and can be assigned a role of a cluster member or a cluster head. A cluster pattern is selected for each communication round based on the node energy levels. Communication rounds take place in predefined or motion-triggered time intervals that are part of the network configuration, and continue until most of the nodes' energy is depleted. The number of communication rounds determines the lifetime of the network: the greater the number of rounds, the longer the network lifetime.

### 3.2.2. Maximum cluster size and pattern generation

The sensor nodes are designed in such a way that the node's data sensing activity is reflected in the node's energy level. The higher the data sensing activity the lower the node's energy. As a result, focusing on the conservation of energy prolongs the network's data sensing capability and its lifetime. From the energy consumption perspective [36], there are two main parameters to consider; hopping energy cost (h), and transmission energy cost (t). Hopping energy cost (h) is the amount of energy required to transmit data from a node to its neighboring node. If the node is a cluster member that is three (3) hops away from its cluster head, for example, it will take 3*h amount of energy to transfer its data to the cluster head. Transmission energy cost (t) is the amount of energy required for a cluster head to transmit its collected data to the base station.
While each WSN network design and application is unique, generally speaking, the communication between sensor nodes consumes less energy than the data transmission to the base station, so clustering optimizes the total energy that it takes to transmit the data collected by the network. Given the network size in terms of the total number of sensor nodes (n), the hopping energy cost (h) and the transmission energy cost (t), the maximum cluster size N for the given network is the cluster pattern that consumes the least amount of communication energy (i.e. the cluster pattern with the minimum total energy cost). The maximum total energy cost for patterns created using different cluster sizes is the sum of the number of cluster heads multiplied by the transmission cost (t) and the number of cluster members' total hops multiplied by the hopping energy cost. For example, if the network with 169 nodes (n = 169) has the hopping energy cost h = 0.01, and transmission energy cost t = 0.2, then the maximum cluster size is N = 19 since the pattern with this cluster size consumes the least amount of communication energy, with total energy cost = 4.580 (see Table 2).

Table 1. Selecting the maximum cluster size

| Network size (n) | Node hop cost (h) | Transmission cost (t) |
|---|---|---|
| *169* | *0.01* | *0.2* |

| Cluster size N | Number of clusters | Number of cluster members with hop-distance to their respective cluster head | | | | | | | Total nodes (n) | Total energy cost |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 hop | 2 hops | 3 hops | 4 hops | 5 hops | 6 hops | 7 hops | | |
| 7 | 25 | 132 | 12 | - | - | - | - | - | 169 | 6.560 |
| 19 | 7 | 42 | 84 | 36 | - | - | - | - | 169 | 4.580 |
| 37 | 7 | 30 | 54 | 78 | - | - | - | - | 169 | 5.120 |

Once the maximum cluster size N is determined, and knowing that the position of the first cluster head is the location of the base station in the center of the network, the (p, q, r) coordinates of the remaining cluster heads and related cluster members can be computed, as outlined in Section 3.1.3. For each cluster size N, there are two concentric cluster patterns that obey the cluster properties as previously described in Section 3.1.2. Those are the patterns with (a, b) and (b, a) distance from a cluster head to the next cluster head, where cluster size N obeys the N(a, b) relation indicated in Section 3.1.2. In the stated equation *a* and *b* are the number of cells between adjacent cluster centers on a 60-degree grid, as described in Section 3.1.3. Figure 7 illustrates the two patterns for cluster size N=19: Pattern A with N(2, 3) = 19 and pattern B with N(3, 2) = 19. This is beneficial since the cluster heads use more energy (transmission energy cost), and this pattern variation enables nodes' role rotation, in order to exhaust nodes' energy more evenly.

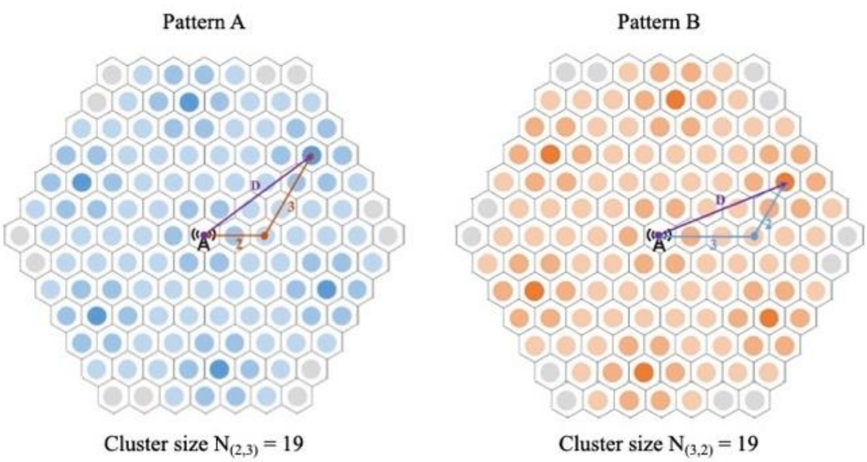


Figure 7. Two patterns for cluster size N = 19

Based on the maximum cluster size N, the remaining patterns with the smaller cluster sizes are generated, and used once the nodes get depleted and can no longer support multi-hops required by the maximum cluster size.

### 3.3. Optimization Model

The optimization model is implemented using a mathematical modeling language AMPL, which is designed to represent and solve complex problems in large-scale mathematical computing, such as optimization and scheduling tasks for extensive applications. The Gurobi solver is used as the optimization solver to expedite the model runs.

The main motivation for employing the hexagonal topology (as outlined in Section 3.1) is the benefits and simplicity it lends for formulating the optimization model. Its unique properties enable global definition of constraints for cluster head selection and cluster member assignment. The ability to model network optimization on a higher level of abstraction results in energy efficiency, interference reduction and scalability of the overall network.

As the number of cluster-heads increases, the more energy is being consumed, driven by the cluster-head transmission energy cost which is typically significantly higher than the cluster-member hopping energy cost. The goal of the optimization model is to start with the maximum cluster size N patterns and only decrease the cluster size once the nodes have been depleted and can no longer support multi-hops required by the larger cluster size(s).

Notation for the network optimization model is defined as follows:

- *Index i* represents the nodes, ranging from 0 to n
- *Index j* represents the patterns, ranging from 0 to p
- *Index k* represents the networks communication time intervals, ranging from 0 to r
- *hop(i,j)* is hop energy required for each cluster member per pattern
- *trans(i,j)* is transmission energy required for each cluster head per pattern
- *Use(j)* is a binary decision variable for selecting a cluster pattern per time interval r
- *h* is a set parameter for hopping energy cost between adjacent cluster members
- *t* is a set parameter for transmission energy cost between cluster head and base station

### 3.3.1. Model Objective and Constraints

The overall optimization objective is maximization of the network's lifetime. Therefore, for each communication time interval the objective is to maximize the network's current energy level ($C_E$), by utilizing decision variable *Use(j)* to select the most energy efficient pattern for the given time interval. Using the terminology above, the network lifetime may be maximized by solving the following maximization problem:

$$Maximize\ C_E: \sum_{i=0}^{n} CurrentInterval(i) - \sum_{i=0}^{n}\sum_{j=0}^{p} Use(j) * (hop(i,j) * h + trans(i,j) * t)$$

, subject to the constraints outlined below.

For each communication time interval, the model objective is solved subject to the following constraints:

- <u>*Constraint 1*</u>: Select only one cluster pattern per time interval.

  $$UseOnePattern: \sum_{j=0}^{p} Use(j) = 1$$

- <u>*Constraint 2*</u>: All cluster heads in selected pattern must have minimum energy required for data transmission to the base station.
  $ClusterheadEnergy\ \{(i,j)\ in\ ClusterHeads\}$:
  $$Use(j) * Intervals(i, CurrentInterval) * trans(i,j) \geq Use(j) * trans(i,j)$$

- <u>*Constraint 3*</u>: Select a pattern with higher cluster head energy levels.
  $HigherEClusterheads\ \{j\ in\ Patterns\}$:
  $$Use(j) * max.min.ch \leq Use(j) * max(min.clusterheads(j))$$

### 3.3.2. Model Algorithm

To tackle this specific optimization problem, a novel algorithm is designed and specifically engineered from the ground up to select the most energy efficient pattern for each time interval in order to optimize the lifetime of the wireless sensor network. The algorithm also considers the two-index, non-linear parameter in Constraint 3 of the optimization and implements a process to make it linear for the purpose of solving the optimization problem stated in Section 3.3.1 (Algorithm 1, lines 3-6 and lines 9-12).

Algorithm 1. Optimization model algorithm pseudocode for the network lifetime

***Input***
Nodes set (index i)
Patterns set (index j)
Intervals set (index k)
*hop(i,j)* matrix, hop energy required for each cluster member per pattern
*trans(i,j)* matrix, transmission energy required for each cluster head per pattern
*ntwke(j,k)* matrix, network energy level for each interval r
*h* is a set parameter for hopping energy cost between adjacent cluster members
*t* is a set parameter for transmission energy cost between cluster head and base station
***Output***
Ntwk_Patterns: array of patterns used for all rounds within the intervals r
Ntwk_Energy: array of network energy levels for all rounds within the intervals r

1. **for** each time interval (round) r in Intervals
2. **if** r = 0 then
3. Let *trans_energy _cost(r)* = 0
4. Identify a cluster head with minimum energy level for each pattern *j*
5. *max_min_ch* = maximum of cluster head minimums from step-4
6. Use *max_min_ch* in Constraint 3
7. Solve Optimization $C_E$
8. **else**
9. Let *trans_energy cost(r) = total_trans_cost(r-1)*
10. Identify a cluster head with minimum energy level for each pattern *j*
11. *max_min_ch* = maximum of cluster head minimums from step-10
12. Use *max_min_ch* in Constraint 3
13. Solve Optimization $C_E$
14. **end if**
15. Display *Use(j)*, pattern selection for current interval r
16. **for** i in Nodes
17. Let *current_pattern_cost(i,r)* = $\sum_{j=0}^{p} hop(i,j) * h + trans(i,j) * t$
18. Let *total_round_cost(i,r) = current_pattern_cost(i,r)*
19. **end for**
20. Let *total_pattern_cost(r)* = $\sum_{i=0}^{n} total\_round\_cost(i,r)$
21. Let *total_trans_cost()] = total_pattern_cost(r-1)* + *total_pattern_cost(r)*
22. Display *total_trans_cost*, to be used in the next interval
23. Add pattern *Use(j)* to *Ntwk_Patterns* array
24. Add $C_E$ optimization result to *Ntwk_Energy* array
25. **if** $C_E$ value < 0 **then** quit the algorithm
26. **end for**
27. Display *Ntwk_TotalRounds*, *Ntwk_Patterns* and *Ntwk_Energy* arrays

## 3.4. Network Simulation

The network simulation was built using Contiki-NG OS Cooja simulator which concentrates on network behavior. Cooja is a wireless sensor network simulator which permits the emulation of real hardware platforms, and can simulate WSN clusters, including the interactions between clustered sensor nodes and cluster heads. Cooja provides the necessary tools and flexibility to simulate various network topologies, communication protocols, and behaviors found in clustered WSNs [40].

The objective of the network simulation for this research is to evaluate the energy efficiency of leveraging clusters in hexagonal network topology, and generating network sensing data to evaluate the effectiveness of the optimization model.

### 3.4.1. Simulation protocols

The simulation is implemented using the Routing Protocol for Low-Power and Lossy Network (RPL) network layer protocol with UDP transportation layer protocol. RPL is designed to provide efficient multi-hop routing in Low-power and Lossy Networks (LLNs), which are characteristic of many IoT and WSN environments. When combined with User Datagram Protocol (UDP), it facilitates the transmission of data packets across the network established by RPL. Essentially, RPL organizes devices into a Destination-Oriented Directed Acyclic Graph (DODAG) based on a set of routing metrics and objectives, optimizing the path for data packet flow to a common destination (such as a cluster-head or sink node), while UDP is used to transport data packets between nodes in this network.

### 3.4.2. Simulation nodes and parameters

In the context of Contiki Cooja, a "mote" is a virtual representation of a physical sensor node as it exists in a real-world WSN. A mote in Cooja encapsulates both the hardware characteristics of a sensor node (such as its microcontroller, radio, and sensors) and its software (the firmware running on the node, including the operating system and application code). This abstraction enables simulation and analysis of the behavior of sensor networks under various conditions without the need for physical hardware. Simulation for this research employs Skymotes, since they support applications based on high data rate sensors and low power networks.

Transmission and interference ranges are critical parameters for accurately modeling how radio signals propagate and how they are affected by distance and other factors in a simulated wireless sensor network. The transmission range defines the maximum distance at which a mote (i.e. node) can successfully transmit a signal to another mote. If two motes are within each other's transmission range, they can directly communicate without the signal being too weak to be detected. This parameter is used to simulate the effective coverage area of a mote's radio transmitter and is set to 14 meters in this simulation. The interference range is the distance within which a mote can cause interference to the communication between other motes, even if it is beyond the direct transmission range. Signals from a mote within this range can interfere with or degrade the quality of communications between other motes that are actively transmitting or receiving data. This parameter is critical for simulating more realistic network behaviors, especially in dense networks where multiple transmissions might overlap. It helps to model scenarios where communications might be corrupted or lost due to interference from nearby motes. In this simulation interference range parameter is set to 20 meters, reflecting real-world interference challenges in WSNs. These and other parameter values are listed in the Table 3.

Table 2. Simulation settings and parameters

| **Parameter** | **Value** | **Description** |
|---|---|---|
| Number of Motes | 127 | Total number of nodes in the network |
| Area Size | D=140m, A=12730m$^2$ | Diameter and m$^2$ area of the simulation area |
| Area Shape | Hexagon | Shape of the simulation area |
| BS Position | Center | Location of the base station |
| Mote Type | Skymote | Node application based on high data rate sensors and low power networks |
| Transmission Range | 14m | Maximum distance for node transmission |
| Interference Range | 20m | Maximum distance for communication interference between the nodes |
| Simulation Time | 2500 rounds | Total duration of simulation |
| Network Protocol | RPL | Routing Protocol for Low-Power and Lossy Network |
| Transportation Protocol | UDP | User Datagram Protocol |

#### 3.4.3. Simulation objective functions

RPL is designed to facilitate routing in constrained networks, and it uses Objective Functions (OFs) to determine the best path for data packets to travel through the network. Therefore, OFs play a crucial role in configuring clusters in a wireless sensor network topology. The Minimum Rank with Hysteresis Objective Function (MRHOF) aims to minimize the rank in the Directed Acyclic Graph (DAG), considering link metrics such as expected transmission count (ETX). It prefers stable, high-quality links to reduce overall network traffic in order to improve reliability. MRHOF may use hysteresis to prevent frequent changes in CH (parent) selection, enhancing network stability. (Jamil, et al., 2019) This OF is used for modeling a network without clusters, and for modeling cluster-heads in the clustered network topology. Objective Function Zero (OF0) is a simpler OF compared to MRHOF, primarily focusing on minimizing hop count, and it is used for modeling cluster-members in the clustered network topology.

### 3.5. Evaluation Approach

#### 3.5.1. Energy efficiency evaluation

Using the simulation implementation characteristics and parameters outlined above, wireless sensor network simulations are configured consisting of 127 nodes (n=127) with and without clusters. The maximum cluster size N is calculated for the network size n=127, as described in Section 3.2.2, yielding the maximum cluster size N=19. Therefore, for the cluster configuration there are two viable cluster sizes used: N=19 and N=7 nodes (Figure 8, Figure 9), yielding four cluster patterns, two for each cluster size, as shown in Section 3.2.2. For the network configuration without clusters the same corresponding network topology is employed where sink nodes are positioned at the cluster-heads locations (Figure 8, Figure 9).

For a larger network size n the maximum cluster size N is also larger yielding a higher number of cluster sizes and related cluster patterns. Nevertheless, the same principles described above apply for the energy efficiency evaluation.

Analysis of simulations compares: (1) the cluster-head transmission energy in clustered topology with sink-nodes transmission energy in non-clustered topology; (2) cluster-member hopping energy in clustered topology with node hopping energy in non-clustered topology; and (3) transmission energy used per packet in all four network topologies in order to evaluate which of the four simulation scenarios for the given hexagonal network (n=127) provides the most energy efficient transmission.

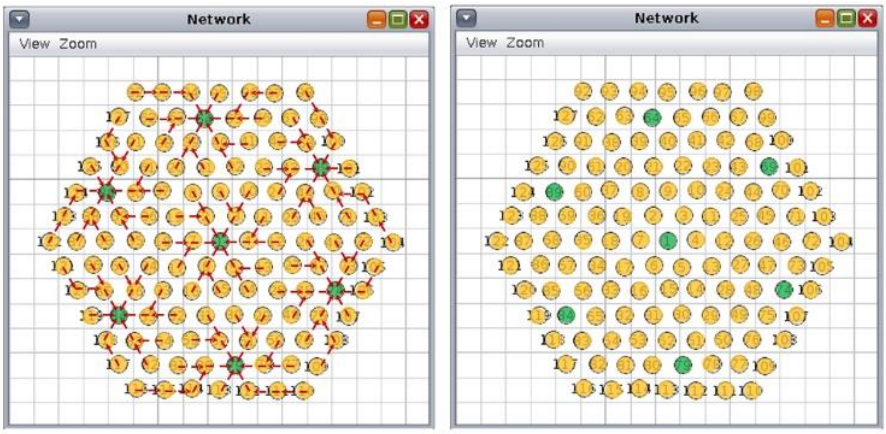


Figure 8. Network with N=19 layout, with clusters and without clusters

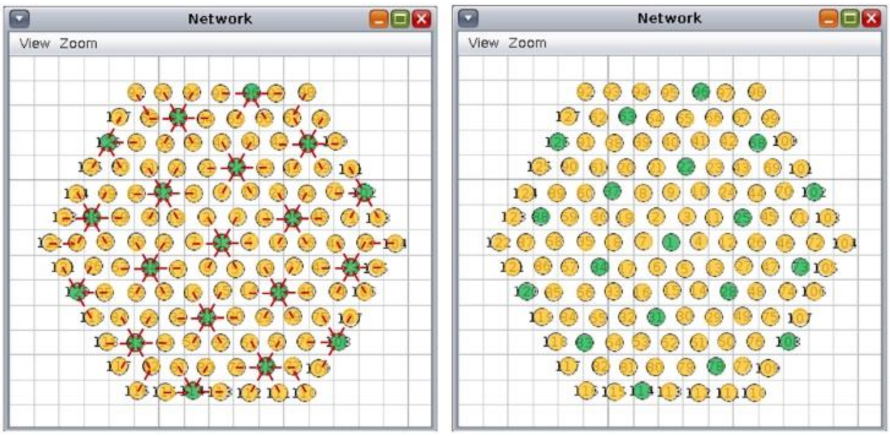


Figure 9. Network with N=7 layout, with clusters and without clusters

### 3.5.2. Optimization model validation

Optimization model validation aims to confirm the simulation results in terms of network energy efficiency. To achieve this evaluation optimization model uses network sensing data generated from simulation, along with the values for the transmission energy and hopping energy parameters.

Network sensing data for the optimization model is generated using the simulation Radio RX % data. This metric represents the percentage of time the radio of a mote is in the receiving (RX) state, actively listening and receiving sensing data and data from other motes. Although receiving data typically consumes less power than transmitting, using the Radio RX % data to generate the network sensing data reflects the real-world scenario. For this research, Radio Rx % from the network simulation (n=127) with clusters of two sizes (N=19 and N=7) was collected and used to generate the network sensing data as an input into the network optimization model.

The average cluster-head transmission energy parameter and the average cluster-member hopping energy parameter from the network simulation (n=127) with clusters of two sizes

(N=19 and N=7) were obtained from simulations and used as the input parameters for the optimization model. Three optimization scenarios for the hexagonal network topology (n=127) were considered: (1) topology with a static cluster size N=19; (2) topology with a static cluster size N=7; and (3) topology with dynamic cluster sizes N=19 and N=7. The results were compared with the network simulation outcome in order to confirm the network scenario that provides the longest network lifetime.

### 3.5.3. Impact of transmission and hopping energy ratio

For dynamic clustering in the hexagonal network topology, cluster-head transmission energy parameter needs to be the same for all cluster sizes (i.e. N=19 and N=7). Similarly, the cluster-member hopping energy parameter needs to be the same for all cluster sizes. These two assumptions are required since a network node can change its role between cluster-head and cluster-member during the lifetime of the network. Analyzing the transmission energy and hopping energy ratio, by using a range of values for both parameters, provides further information about dynamic clustering effectiveness.

## 4. RESULTS & ANALYSIS

This section provides an overview of key metrics used for measuring clustering effectiveness in hexagonal network topology, and explores impacts of transmission energy cost and hopping energy cost on benefits of clustering in hexagonal topology for WSNs. As indicated in the previous section, simulations are performed using Contiki Cooja simulator, and optimization model is created in AMPL using Gurobi as an optimization solver.

This work is centered around determining the optimal cluster size and related cluster pattern using a mathematical optimization model by maximizing network's lifetime. Once the maximum cluster size N is identified, all cluster sizes up to size N are considered for pattern generation. The optimal pattern is selected for each data sensing time interval until most of the nodes are depleted. Therefore, there are two key evaluation metrics that are used: (1) transmission energy cost per packet when evaluating simulations; and (2) the number of rounds (i.e. time intervals) in the optimization model before the total network's energy is depleted.

For example purposes, this paper considers the wireless sensor network with 127 nodes (n=127), with maximum cluster size N=19, and consequently two cluster sizes N=19 and N=7, yielding four cluster patterns, two for each cluster size. For networks with a larger size n, the maximum cluster size N increases, resulting in a greater variety of cluster sizes and associated patterns. For example, consider a WSN with n=547 nodes; its maximum cluster size is N=91. Therefore, for the network size n=547 the viable cluster sizes up to and including N=91 are: N=7, N=19, N=37, N=61, and N=91. These five cluster sizes yield ten cluster patterns, two for each cluster size, as outlined in Section 3.1.3. However, regardless of the network size n, the principles outlined previously still govern the evaluation of energy efficiency and network lifetime.

### 4.1. Evaluation of energy efficiency

Following the approach in Section 3.5.1, four distinct wireless sensor network simulations are configured consisting of 127 nodes (n=127) with and without clusters. Analysis of simulations compares: (1) the cluster-head transmission energy in clustered topology with sink-nodes transmission energy in non-clustered topology; (2) cluster-member hopping energy in clustered topology with node hopping energy in non-clustered topology; and (3) transmission energy used per packet in all four network topologies, to evaluate which of the four simulation scenarios for the given hexagonal network (n=127) provides the most energy efficient transmission.

As shown in Table 4, when comparing the network configuration with cluster size N=19 with its counterpart configuration without clustering (Figure 8), the total number of packets transmitted in the same time period is 2.13% higher in the network with clusters. Additionally, the average transmission energy cost per packet is lower in the network with clusters (0.000842). In the case of cluster size N=7, comparing the network configuration with clusters (N=7) with its counterpart configuration without clustering (Figure 9), the total number of packets transmitted in the same time period is 7.27% higher in the network with clusters (Table 4). Additionally, the average transmission energy cost per packet is lower in the network with clusters (0.000833). Therefore, the clustering performs better for both network layouts (N=19 and N=7), and in this network, cluster size N=7 provides the longest network lifetime, given the lowest average transmission energy cost per packet.

Table 3. Average transmission energy costs per packet for various network configurations

| Network size (n = 127) | Total Packets | Trans. Energy per Packet | Packets % |
|---|---|---|---|
| With Clusters: N=19 | 2825 | 0.00084248 | 2.13% |
| Without Clusters: N=19 | 2766 | 0.00085322 | |
| With Clusters: N=7 | 2820 | 0.00083333 | 7.27% |
| Without Clusters: N=7 | 2629 | 0.00083682 | |

The average cluster-head transmission energy cost and the average cluster-member hopping energy cost from simulations above with cluster sizes N=19 and N=7 are used to run and validate the optimization model.

## 4.2. Validation of Optimization Model

Adhering to the method described in Section 3.5.2 simulations along with the network data from Section 4.1 are utilized to generate the network sensing data that is used as an input into the optimization model. Additionally, as previously mentioned, the two key simulation parameters utilized as the input to the optimization model are: the average cluster-head transmission energy cost (0.3400 and 0.12368 respectively) and the average cluster-member hopping energy cost (0.10208 and 0.07167 respectively) for cluster sizes N=19 and N=7, as shown in Table 5. The optimization model results are then compared with the simulation results obtained in Section 4.1. Three optimization scenarios for the hexagonal network topology (n=127) were considered: (1) topology with a static cluster size N=19; (2) topology with a static cluster size N=7; and (3) topology with dynamic cluster sizes N=19 and N=7. As indicated in Table 5 and Figure 10, optimization results were compared and the topology with a static cluster size N=7 provides the longest network lifetime (i.e. has a maximum number of rounds). As shown, the network optimization model has the same outcome as the network simulation result.

Table 4. Total number of rounds for clustered network configurations

| Network size (n = 127) | Transmission Energy | Hopping Energy | Hop. E and Trans. E Ratio | Total Rounds |
|---|---|---|---|---|
| Static Clusters: N=19 | 0.34000 | 0.10208 | 0.30 | 1347 |
| Static Clusters: N=7 | 0.12368 | 0.07167 | 0.58 | 1878 |
| Dynamic Clusters: N=19 & N=7 | above | above | n/a | 1430 |

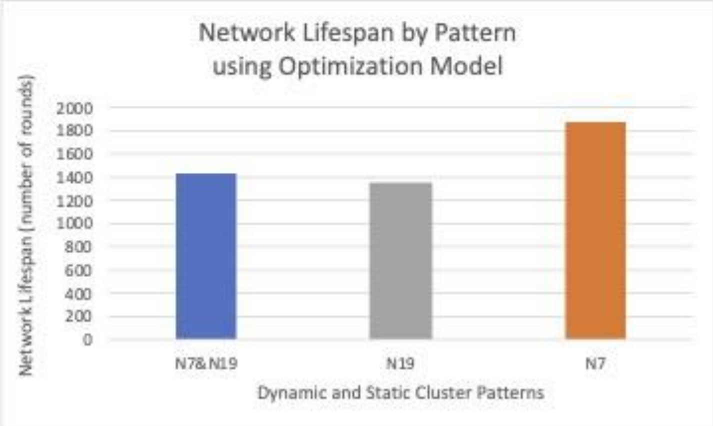


Figure 10. Network lifetime by clustering pattern

### 4.3. Impact of transmission and hopping energy ration

Network simulation results and optimization model output both demonstrate that clustering improves the network lifetime, specifically when using static clustering with cluster size N=7 for this network example. As indicated in Table 5, the hopping energy cost and transmission energy cost ratio for the cluster pattern with cluster size N=7 is 0.58 which is generally high for large scale WSNs which typically have a ratio in 0.10-0.20 range [16]. Further examination is required to determine when the dynamic clustering of all viable patterns (N=19 and N=7) provides further benefits and even longer network lifetime. Using the procedure specified in Section 3.5.3 to further analyze the cluster-member hopping energy cost and cluster-head transmission energy cost ratio for dynamic clustering (N=19 and N=7) vs static clustering (N=7), Table 6 outlines optimization model results using a range of values for both parameters.

Table 5. Network lifetime for a range of transmission and hopping energy values

| | **Hopping Energy** | **Transmission Energy** | **Hop. E and Trans. E Ratio** | **Total Rounds Dynamic Clustering N7 & N19** | **Total Rounds Static Clustering N7** | |
|---|---|---|---|---|---|---|
| 1 | 0.14 | 0.2 | 0.70 | 1194 | 2178 | |
| 2 | 0.12 | 0.2 | 0.60 | 1316 | 2005 | 58.00% |
| 3 | 0.10 | 0.2 | 0.50 | 1449 | 1871 | |
| 4 | 0.08 | 0.2 | 0.40 | 1585 | 1753 | 33.50% |
| 5 | 0.06 | 0.2 | 0.30 | 1744 | 1649 | |
| 6 | 0.04 | 0.2 | 0.20 | 1940 | 1556 | |
| 7 | 0.02 | 0.2 | 0.10 | 2235 | 1475 | |

As the network's cluster-member hopping energy cost and cluster-head transmission energy cost ratio decreases, the benefit of using static clustering also decreases while the effectiveness of dynamic clustering increases (Figure 11).

Therefore, the dynamic clustering further improves network lifetime for the WSNs where the cluster-member hopping energy cost and cluster-head transmission energy cost ratio is 33.5% or less as shown in Figure 12. With older hierarchical protocols such as LEACH and HEED, forming the clusters in a wireless sensor network has traditionally been costly in terms of energy consumption. However, with the design advancement of efficient Objective Functions for RPL routing protocol, the objective functions assignment can now be dynamic, supporting multiple clustering patterns, and therefore, more energy efficient when it comes to the energy cost of clustering. [32-34]

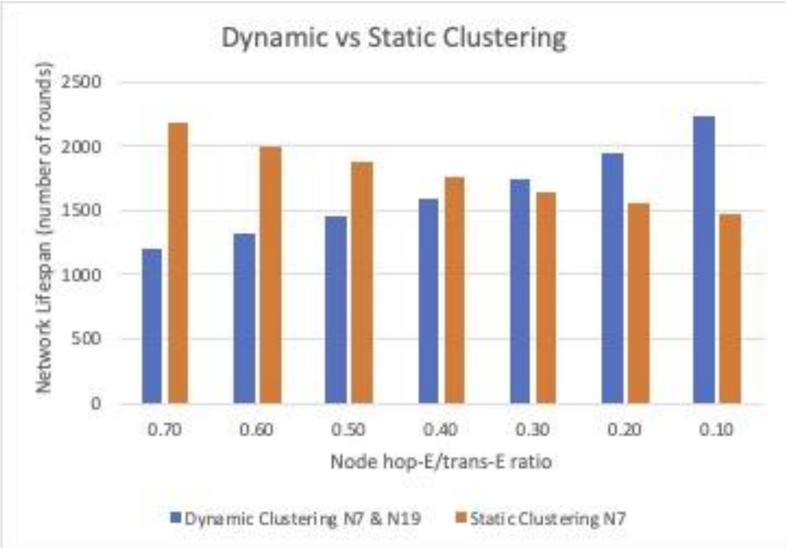


Figure 11. Network lifetime with dynamic vs static clustering

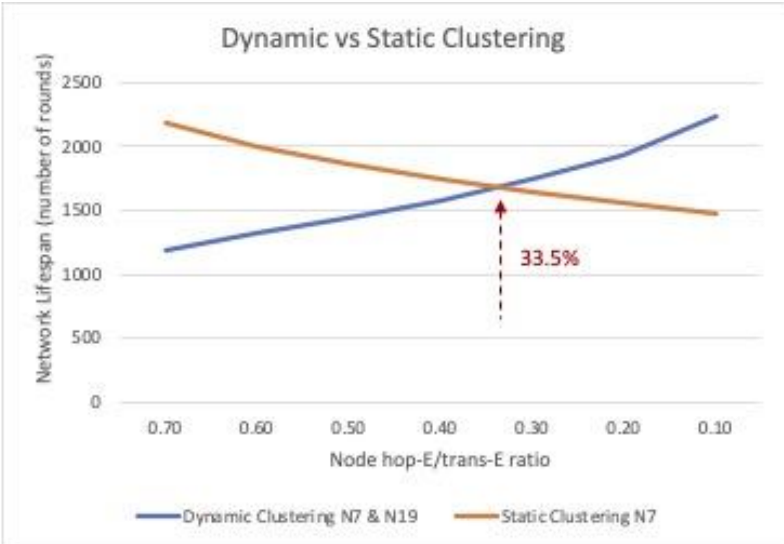


Figure 12. Network lifetime with hopping energy and transmission energy ratio

## 5. CONCLUSION & FUTURE RESEARCH

This research demonstrates that WSNs with hexagonal network topology can benefit from clustering which improves network lifetime, and therefore, enhances WSNs reliability by reducing total network energy consumption. Additionally, dynamic clustering further improves network lifetime for the WSN where the cluster-member hopping energy cost and cluster-head transmission energy cost ratio is 33.5% or less. Future research in this area will focus on incorporating multistate (active, idle, inactive, fail) nodes and their energy efficiency impact on optimization of static and dynamic clustering in hexagonal network topology. Moreover, this work will benefit from Deep Reinforcement Learning to enhance cluster sizing and matching, and learn from the network's data history, which will help automate and improve WSN quality.

## REFERENCES

[1] Li, W., Zhu, C., Leung, V. C., Yang, L. T., and Ma, Y.: Performance comparison of cognitive radio sensor networks for industrial IoT with different deployment patterns. IEEE Systems Journal, 11, 1456-1466. (2017). https://doi.org/10.1109/JSYST.2015.2500518

[2] Li, J., Tao, Y., Yuan, K., Tang, R., Hu, Z., Yan, W., and Liu, S.: Fruchterman–Reingold hexagon empowered node deployment iLinn wireless sensor network application. National Library of Medicine, Sensors, 22(14), 5179. (2022). https://doi.org/10.3390%2Fs22145179

[3] Tang, R., Qian, X., and Yu, X.: On virtual-force algorithms for coverage-optimal node deployment in mobile sensor networks via the two-dimensional Yukawa crystal. International Journal of Distributed Sensor Networks, 15(9). (2019). https://doi.org/10.1177/1550147719864888

[4] Xu, Z., Chen, L., Chen, C., and Guan, X.: Joint Clustering and Routing Design for Reliable and Efficient Data Collection in Large-Scale Wireless Sensor Networks. IEEE Internet of Things Journal, 3(4). (2016). https://doi.org/10.1109/JIOT.2015.2482363

[5] Choi J., Bang J., Kim, L. H., Ahn, M., Kwon, T.: Location-Based Key Management Strong Against Insider Threats in Wireless Sensor Networks. IEEE Systems Journal, 11(2), 494-502. (2017). https://doi.org/10.1109/JSYST.2015.2422736

[6] Chakraborty, S., Goyal, N.K., Mahapatra, S., and Soh, S.: A Monte-Carlo Markov chain approach for coverage-area reliability of mobile wireless sensor networks with multistate nodes. Reliability Engineering & System Safety, 193, 106662. (2020). https://doi.org/10.1016/j.ress.2019.106662

[7] Cerotti, D., Gribaudo, M., and Bobbio, A.: Markovian agents models for wireless sensor networks deployed in environmental protection. Reliability Engineering and System Safety, 130,149-158. (2014). https://doi.org/10.1016/j.ress.2014.05.010

[8] Xu, B., Liu, T., Bai, G., Tao, J., Zhang, Y., Fang, Y.: A multistate network approach for reliability evaluation of unmanned swarms by considering information exchange capacity. Reliability Engineering & System Safety, 219, 108221. (2022). https://doi.org/10.1016/j.ress.2021.108221

[9] Hriez, S., Almajali, S., Elgala, H., Ayyash, M., Salameh, H. B.: A Novel Trust-Aware and Energy-Aware Clustering Method That Uses Stochastic Fractal Search in IoT-Enabled Wireless Sensor Networks. IEEE Systems Journal, 16(2), 1-12. (2022). https://doi.org/10.1109/JSYST.2021.3065323

[10] Yadawad, S., Joshi, S.M.: Efficient energy consumption and fault tolerant method for clustering and reliable routing in wireless sensor network. Peer-to-Peer Networking and Applications, 17 1552-1568. (2024). https://doi.org/10.1007/s12083-024-01664-4

[11] Ablowitz, M. J., Zhu, Y.: (2012). Nonlinear Waves in Shallow Honeycomb Lattices. SIAM Journal on Applied Mathematics, 72(1), 240–260. (2024). https://doi.org/10.1137/11082662X

[12] Larsson, L. J., Choksi, R., Nave, J. C.: (2016). Geometric Self-Assembly of Rigid Shapes: A Simple Voronoi Approach. SIAM Journal on Applied Mathematics, 76(3), 1101–1125. (2024). https://doi.org/10.1137/15M1034167

[13] Brodsky, I.: H3: Uber's hexagonal hierarchical spatial index. Uber Blog, Engineering. https://www.uber.com/blog/h3/ (2018). Accessed 11 Jul 2024

[14] Qin, Z., Tang, X., Jiao Y., Zhang, F., Xu, Z., Zhu, H., Ye, J.: Ride-hailing order dispatching at DiDi via reinforcement learning. INFORMS Journal on Applied Analytics, 50(5): 272-286. (2020). https://doi.org/10.1287/inte.2020.1047

[15] Kardos, P., Palagyi, K.: On topology preservation of mixed operators in triangular, square, and hexagonal grids. Discrete Applied Mathematics, 216(2), 441-448. (2017). https://doi.org/10.1016/j.dam.2015.10.033

[16] Kim, J., Lee, D., Hwang, J., Hong, S., Shin, D., Shin, D.: Wireless Sensor Network (WSN) Configuration Method to Increase Node Energy Efficiency through Clustering and Location Information. Symmetry and Asymmetry in Communications Engineering, 13(390). (2021). https://doi.org/10.3390/sym13030390

[17] Njoya, A.N., Thron, C., Awa, M. N., Abba-Ari, A. A., Gueroui, A. M.: Power-saving system designs for hexagonal cell based wireless sensor networks with directional transmission. Journal of King Saud University - Computer and Information Sciences, 34(10), 7911-7919. (2022). https://doi.org/10.1016/j.jksuci.2022.07.008

[18] Singh, S., Anand, V., Yadav, S.: Trust based clustering and routing in WSNs using DST WOA. Peer-to-Peer Networking and Applications,17 1486-1498. (2024). https://doi.org/10.1007/s12083-024-01651-9

[19] Dargie, W., Poellabauer, C.: Fundamentals of wireless sensor networks: Theory and practice. John Wiley & Sons, Ltd. (2010). http://dx.doi.org/10.1002/9780470666388

[20] Ko J. G., Lu, C., Srivastava, M.B., Stankovic, J. A., Terzis, A., Welsh, M.: Wireless sensor networks for healthcare. Proceedings of the IEEE, 98(11),1947–60. (2010). https://doi.org/10.1109/JPROC.2010.2065210
[21] McGrath, M. j., Scanaill, C. N.: Sensor technologies: Healthcare, wellness and environmental applications. Apress. (2013). https://doi.org/10.1007/978-1-4302-6014-1
[22] The Evolution of Wireless Sensor Networks.: Silicon Laboratories Inc. https://www.silabs.com/documents/public/white-papers/evolution-of-wireless-sensor-networks.pdf (2013). Accessed 6 June 2024
[23] Tyagi, S., Kumar N.: A systematic review on clustering and routing techniques based upon LEACH protocol for wireless sensor networks. Journal of Network and Computer Applications, 36(2), 623-645. (2013). https://doi.org/10.1016/j.jnca.2012.12.001
[24] Gupta, P., Sharma, A. K.: Clustering-based heterogeneous optimized-HEED protocols for WSNs. Soft Computing, 24, 1737–1761. (2020). https://doi.org/10.1007/s00500-019-04000-8
[25] Hematkhah, H., Kavian, Y. S.: DCPVP: Distributed clustering protocol using voting and priority for wireless sensor networks. Sensors, 15(3), 5763-5782. (2015). https://doi.org/10.3390/s150305763
[26] Wang, J., Cao, Y. T., Xie, J. Y., Chen, S. F.: Energy efficient backoff hierarchical clustering algorithms for multi-hop wireless sensor networks. Journal of Computer Science and Technology, 26(2), 283-291. (2011). https://doi.org/10.1007/s11390-011-9435-4
[27] Samiayya, D., Radhika, S., Chandrasekar, A.: An optimal model for enhancing network lifetime and cluster head selection using hybrid snake whale optimization. Peer-to-Peer Networking and Applications, 16 1959-1947. (2023). https://doi.org/10.1007/s12083-023-01487-9
[28] Gao, X., Zhu, X., Li, J., Wu, F., Chen, G., Du, D.: A Novel Approximation for Multi-Hop Connected Clustering Problem in Wireless Networks. IEEE/ACM Transactions on Networking, 25(4). (2017). https://doi.org/10.1109/TNET.2017.2690359
[29] Amini N., Vahdatpour, A., Xu, W., Gerla, M., Sarrafzadeh M.: Cluster size optimization in sensor networks with decentralized cluster-based protocols. Computer Communications 35(2), 207–220. (2012). https://doi.org/10.1016%2Fj.comcom.2011.09.009
[30] Tian, X., Zhu, Y., Chi, K., Liu, J., Zhang, D.: Reliable and energy efficient data forwarding in industrial wireless sensor networks. IEEE Systems Journal, (11)3, 1424-1434. (2017). https://doi.org/10.1109/JSYST.2015.2466696
[31] Lin, H., Üster, H.: Exact and Heuristic Algorithms for Data-Gathering Cluster-Based Wireless Sensor Network Design Problem. IEEE/ACM Transactions On Networking, 22(3). (2014). https://doi.org/10.1109/TNET.2013.2262153
[32] Kuwelkar, S., Virani, H.: Design of an Efficient RPL Objective Function for Internet of Things Applications. International Journal of Advanced Computer Science and Applications, 12(6). (2021). https://doi.org/10.14569/IJACSA.2021.0120625
[33] Zaatouri, I., Alyaoui, N., Guiloufi, A.B., Sailhan, F., Kachouri, A.: Design and Performance Analysis of Objective Functions for RPL Routing Protocol. Wireless Personal Communications, 124, 2677-2697. (2022). https://doi.org/10.1007/s11277-022-09484-6
[34] Zhao, M. Ho, I.W., Chong, P.H.: An Energy-Efficient Region-Based RPL Routing Protocol for Low-Power and Lossy Networks. IEEE Internet of Things Journal, 3(6), 1319-1333. (2016). http://doi.org/10.1109/JIOT.2016.2593438
[35] [35] Pirinen, P.: Capacity analysis of co-channel interference limited TDMA and novel hybrid TDMA/CDMA cellular systems. Licentiate Thesis. University of Oulu, Department of Electrical Engineering, 82. https://www.researchgate.net/publication/258927075_Capacity_analysis_of_co-channel_interference_limited_TDMA_and_novel_hybrid_TDMACDMA_cellular_systems (1998). Accessed 11 April 2024
[36] Liu, X., Wu, J.: A Method for Energy Balance and Data Transmission Optimal Routing in Wireless Sensor Networks. Sensors, 19(13), 3017. (2019). https://doi.org/10.3390/s19133017
[37] Hoang, D. C., Yadav, P., Kumar, R., Panda, S. K.: Real-time implementation of a harmony search algorithm-based clustering protocol for energy-efficient wireless sensor networks. IEEE Transactions on Industrial Informatics, 10(1), 774-783. (2014). https://doi.org/10.1109/TII.2013.2273739
[38] Deng, Y., Han, C., Guo, J., Li, L., Sun, L.: Online missing data imputation using virtual temporal neighbor in wireless sensor networks. Wireless Communication and Mobile Commuting, 2022(4909476). (2022). https://doi.org/10.1155/2022/4909476

[39] Jamil, M., Khan, D., Saleem, A., Mehmood, K., Iqbal, A.: Comparative Performance Analysis of RPL for Low Power and Lossy Networks based on Different Objective Functions. International Journal of Advanced Computer Science and Applications, 10(5). (2019). http://doi.org/10.14569/IJACSA.2019.0100524

[40] Oikonomou, G., Duquennoy, S., Elsts, A., Eriksson J., Tanaka, Y., Tsiftes, N.: The Contiki-NG open source operating system for next generation IoT devices. SoftwareX, 18. (2022). https://doi.org/10.1016/j.softx.2022.101089

[41] Rajarajeswari, P.L., Devi B.V., Latha A. M.: Hybrid Termite Queen and Walrus Optimization Algorithm-based energy efficient cluster-based routing with static and mobile sink node in WSNs. Peer-to-Peer Networking and Applications, 18(8). (2025). https://doi.org/10.1007/s12083-024-01848-y

[42] Pan, X., Dang, Y., Wang, H., Hong, D., Li, Y., Deng.: Resilience model and recovery strategy of transportation network based on travel OD-grid analysis. Reliability Engineering & System Safety, 223, 108483. (2022). https://doi.org/10.1016/j.ress.2022.108483

[43] Alsuwat, H., Alsuwat, E.: Energy aware and efficient cluster head selection and routing in wireless sensor networks using improved artificial bee Colony algorithm. Peer-to-Peer Networking and Applications, 18(65). (2025). https://doi.org/10.1007/s12083-024-01810-y


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