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Wireless Sensor Network (WSN) Energy-Efficient Clustering and Routing: Evaluating Kepler's Algorithm Alongside K-Means

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ABSTRACT: Wireless Sensor Networks (WSNs) find applications in a broad spectrum of fields, including but not limited to military surveillance and environmental monitoring, where energy efficiency is a key performance indicator because of sensor node power constraint. Implementation of low energy-consumption clustering and routing protocols is pivotal in optimizing network life by minimizing energy consumption. This paper discusses the collaboration of Kepler's Algorithm with the K-means clustering algorithm for improving energy efficiency in WSNs. Kepler's Algorithm, which is planetary motion dynamics-based, is utilized in the best route selection, while the K-means algorithm is utilized with the aim of enhancing energy savings through efficient clustering of sensor nodes. Extensive experimental work was carried out by simulating the environment of a WSN and analyzing major parameters such as energy consumption, network lifetime, and data transmission efficiency. The hybrid method demonstrated dramatic improvement compared to conventional methods with enhanced energy efficiency and extended network lifetime. The findings indicate the efficacy of employing Kepler's Algorithm with K-means clustering as an efficient solution for energy efficient routing and clustering in WSNs.

KEYWORDS: Kepler's Algorithm, K-means, Clustering, Wireless sensor network

1. INTRODUCTION

Wireless Sensor Networks (WSNs) have shown their importance in a wide range of applications, including but not limited to environmental monitoring, healthcare, agriculture, and military tracking. WSNs are composed of geographically distributed sensor nodes that sense data and transmit it to central processing nodes. The energy limitations of these sensor nodes, however, present great challenges to the lifetime and reliability of WSNs [1][2].

Energy efficiency is very important in WSNs because replacing or recharging batteries of sensor nodes is normally impossible. Clustering techniques have been widely employed to enhance energy efficiency by dividing sensor nodes into clusters to reduce communication overhead and allocate energy consumption equally among nodes [3][4]. Some clustering algorithms targeting the optimization of energy consumption and network lifetime have been introduced in recent studies [5][6].

One of the most popular unsupervised learning algorithms, K-means clustering has also been utilized very successfully in WSNs to design energy-efficient clusters. Clustering the sensor nodes geographically, K-means minimizes intra-cluster distances and thus conserves less energy for data transmission [7][8]. Modifications of the basic K-means algorithm, such as combining it with other optimization techniques, have also been proven to be very useful in conserving even more energy [9][10].

Routing protocols play a critical role in determining the energy efficiency of WSNs. New methods based on natural phenomenon-inspired and optimization techniques have been introduced to discover energy-efficient paths. For instance, swarm intelligence-based routing and fuzzy logic-based routing protocols have exhibited improved performance in terms of energy usage as well as network longevity [11][12]. These advances point toward the possibility of utilizing clustering and routing algorithms together in a combined manner to enhance the overall WSN performance.

This study tries to assess the integration of Kepler's Algorithm and the K-means clustering process in order to realize enhanced energy efficiency in WSNs. By combining the merits of the two algorithms, the study tries to propose a hybrid algorithm that maximizes clustering and routing operations. The proposed method may possibly eliminate the vulnerability of current mechanisms and aid in the development of more energy-efficient mechanisms in WSNs [13][14].

The primary goal of this research is to analyze and validate the efficiency of the integration of Kepler's Algorithm and K-means clustering algorithm. Through the simultaneous integration of these two methods, this study seeks to solve the limitations and drawbacks associated with conventional clustering and routing protocols. This paper provides a thorough experimental observation and performance comparison, corroborating significant energy efficiency, network lifespan, and data transmission efficiency improvements, hence making significant contributions towards WSN technology [15][16].

2. LITERATURE REVIEW

The past literature in Wireless Sensor Networks (WSNs) points out a few clustering and routing protocols to enhance energy efficiency. Conventional algorithms such as LEACH and HEED have remained the central clustering-based routing protocols, making significant contributions to energy efficiency through cluster head rotation and energy-efficient node selection [17][18]. However, these algorithms are not perfect, particularly concerning uneven energy drain across nodes, eventually leading to premature network partitioning and reduced overall lifetime [19][20].

In recent times, the K-means clustering technique has been extensively researched based on its computational simplicity and ability to efficiently reduce intra-cluster communication distances. Numerous K-means variants have been suggested to alleviate its own set of limitations, for instance, initial condition sensitivity and imbalance in cluster size. For instance, researchers have suggested algorithms that integrate K-means and optimization algorithms like particle swarm optimization (PSO) and genetic algorithms (GA), enhancing efficiency in clustering as well as energy conservation by leaps and bounds [21][22].

Routing protocols play a major role in deciding overall energy usage for WSNs. Optimization-based routing techniques like swarm intelligence and bio-inspired algorithms have been identified in previous studies to improve network lifetime as well as routing reliability. Adaptive solutions like these provide which change routes dynamically based on available energy and network conditions, thus improving operational lifetimes of sensor networks [23][24].

Modern research has centered around new methods such as Kepler's Algorithm, where celestial mechanics-drawn low-energy routing is utilized. Kepler's algorithm uses elliptical orbit theory in calculating data transportation optimal routes so that the usage of energy is optimized with stable and predictable routes [25][26]. Route predictability is one such benefit that the algorithm provides, particularly when utilized in WSN where reliability and energy efficiency is a priority.

Even though large strides have been taken, there remain deficiencies in the concurrent utilization of clustering and newer routing algorithms. More specifically, combined use of K-means clustering and Kepler's Algorithm has not been explored extensively, but promising suggestions are available that their concomitant usage would be able to surpass existing limitations and provide the highest energy efficiency. This paper intends to bridge this gap by presenting a detailed study and demonstrating the potential of this hybrid method towards improving network lifetime and operational efficiency in WSN [27][28].

3. THEORETICAL BACKGROUND

3.1 K-means Clustering Algorithm

K-means clustering is a partitioning algorithm widely used for data analysis and network clustering due to its simplicity and utility. It attempts to partition n observations into k groups by projecting each observation into the closest cluster's mean, refining the clusters iteratively until they have converged [29][30].

Minimize J

$$= \sum_{i=1}^{k} \sum_{x_j \in C_i} \left\| x_{j-}\mu_i \right\|^2 \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots. (1)$$

Where:

- K=Number of clusters (predefined).
- C_i= Set of nodes in the i^{th} cluster.
- x_j= Coordinates of the i^{th} sensor node.
- μ_i= Centroid (CH) of the i^{th} cluster.

2. Node Assignment Phase

Each sensor node x_j is assigned to the nearest CH based on Euclidean distance:

$$C_i = \left\{ x_j : \left\| x_{j-}\mu_i \right\|^2 \leq \left\| x_{j-}\mu_i \right\|^2 \forall l \neq i \right\}$$

3. Centroid Update Phase

Recalculate CH positions as the mean of all nodes in their cluster

$$\mu_i = \frac{1}{|C_i|} \sum_{x_j \in C_i} x_j \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (2)$$

1. Residual Energy-Based CH Selection

After clustering, elect the node with the **highest remaining energy** as CH of using the centroid

$$CH_i = \underset{x_i \in C_i}{argmax}\, E_{residual}(x_j) \dots\dots\dots\dots\dots\dots\dots\dots (3)$$

2. Dynamic Cluster Head Rotation

- Periodically re-elect CHs to distribute energy consumption.
- Time intervals can be fixed or adaptive based on energy depletion rates.

3. Distance-Energy Hybrid Metric

$$C_i = \left\{ x_j : \alpha \left\| x_{j-}\mu_i \right\|^2 + (1 - \alpha) \frac{1}{E_{residual}(x_j)} \text{ is minimized} \right\} \dots\dots\dots\dots (4)$$

Where $\alpha \in [0,1]$ weights distance vs. energy

$$CH_i = \underset{x_i \in C_i}{argmax}\, E_{residual}(x_j) \dots\dots\dots\dots\dots\dots\dots\dots (5)$$

3.2 Kepler's Algorithm

Kepler's Algorithm takes inspiration from planetary motion in celestial mechanics, which follows elliptical orbits based on Kepler's laws. Kepler's Algorithm employs the patterns of elliptical orbits to establish efficient routing routes in sensor networks to achieve overall energy consumption with minimum use and improve communication quality [31][32].

Kepler's first law: Planets orbit the Sun in an elliptical orbit with a focal point. The law explains the orbits by which planets revolve around the Sun. Figure 3 demonstrates the elliptical nature of the paths. Since both ellipses and circles have approximately the same form, both contain two focal points. One of the focal points located in the middle is where the sun lies. Eccentricity, represented by the letter e, is a value that indicates the degree to which an ellipse appears to be flat. Center-to-focus distance divided by semi-major axis distance yields eccentricity (e). Special cases are a circle (e = 0) and a line segment (e = 1). Figure 4 has many oval shapes.

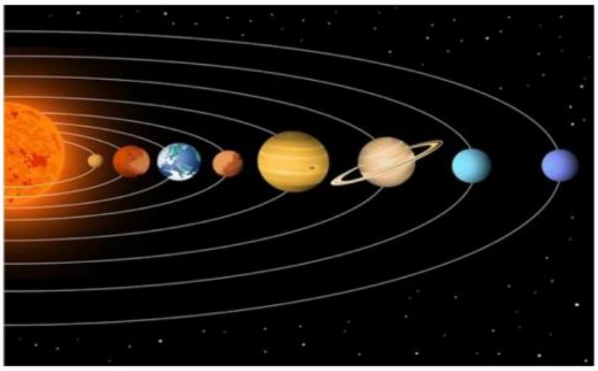

Figure 3. The movement of the planet around the sun in an elliptical orbit [9].

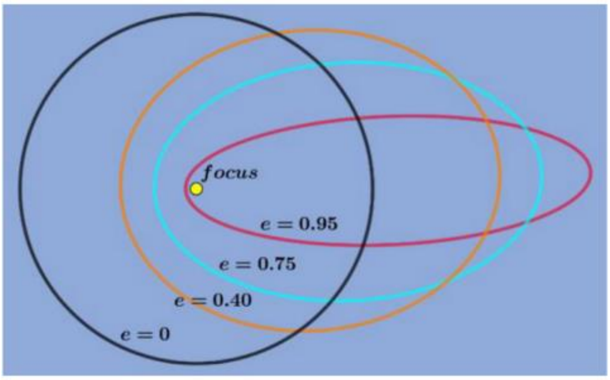

Figure 4. Different cases of oval shapes [9].

Kepler's Second Law: Equal areas are swept away in equal times by a line joining a planet to the Sun. The velocity of a planet's motion in space is always changing, and this law defines the velocity of a planet's motion when it revolves around the Sun. When a planet is close to the sun, its speed increases and when it is travelling away from the sun, its speed diminishes. If, however, a fictional line was drawn from the planet's center to the Sun's center, it would intersect in the same region at the same intervals. The vis-viva equation in equation (2) can be used to determine the speed of the planet as it orbits the Sun.

$$V = \left[\mu(M_S + m)\left(\frac{2}{R} - \frac{1}{a}\right)\right]^{\frac{1}{2}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

Where M_S and m represent the mass of the Sun and a planet, respectively. R is the Euclidean distance between the Sun and a planet currently. μ is the universal gravitational constant and a is the semi-major axis of the circuit.

Kepler's third law: for any planet, the square of the period of any planet is proportional to the cube of the semi major axis of its orbit. It can be expressed mathematically in the form of the equation (6):

$$T^2 = \left[\frac{4\pi^2}{\mu(M_S+m)}\right] a^3 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

where T is the period of the orbiting object (the time required to complete one orbit), a is the semi major axis of the orbit, μ is the universal gravitational constant, M_s is the mass of the Sun, and m is the mass of planet a. The pseudocode of the algorithm is shown in Figure 4.

```
Input: N, T_max, μ_0, γ, T̄.
Initialization.
Evaluation.
Identifying the best-so-far solution X⃗_S.
while (t < T_max)
    Update e, best(t), worst(t), and μ(t).
    for i = 1:N
        Calculate R_i(t) using (5).
        Calculate F_{g_i}(t) using (4).
        Calculate V_i(t) using (12).
        r, r_1: Two numbers selected at random in (0, 1).
        if r > r_1 /* Update position of the planet*/
            Update X⃗_i(t) using (23).
        else /*update the distance between the planet and the sun*/
            Update X⃗_i(t) using (24).
        End if
        Apply (28)
        t = t + 1
    End for
End while
Output: X⃗_S
```

Figure 4. Pseudo-code of KOA steps [9]

The use of Kepler's algorithm to locate the nodes in WSN and cluster them to improve the energy in the routing protocol will have positive impacts. During the clustering phase, any device whose mean value is closest to the current device specification is added to the cluster. The process of working is that during the clustering phase; after forming the clusters, each cluster chooses a cluster head. The cluster head aggregates messages from all devices in its cluster and sends them to the base station. Hence, clusters perform intensive processing and energy expenses on their clusters and assist in constructing routes. But this results in nodes depleting energy levels quickly. To avoid damaging nodes due to battery power drain, the proposed method re-chooses a new cluster head after some time. In each cycle start, the nodes are selected based on the remaining battery life. Rotation of nodes leads to routing requests being evenly distributed over devices and thus the network lifetime is enhanced. Since all devices will have the same energy in round one, branches are chosen randomly in round one.

4. PROPOSED METHODOLOGY

Proposed methodology combines the K-means algorithm for clustering and Kepler's algorithm for maximum energy-efficient clustering and routing in WSNs. The methodology proceeds with some steps:

Step 1: Network Initialization

The nodes are randomly deployed in the sensing region, and initial network values like energy levels, node locations, and communication zones are created.

Step 2: Clustering by K-means Nodes is partitioned into clusters using the K-means algorithm. Initially, k cluster centroids are randomly selected. Nodes are assigned to the nearest centroid, and new centroids are updated iteratively until convergence.

Step 3: Election of Cluster Heads Cluster heads are selected using residual energy and proximity to the centroid. This approach achieves balanced energy in the network.

Step 4: Optimization of Routes using Kepler's Algorithm. Kepler's Algorithm optimizes data transmission from the cluster heads to the sink node in the most efficient manner possible. Energy efficient elliptical routes are computed that provide secure and stable communication.

Step 5: Data Transmission and Network Operation Data is transmitted by the sensor nodes to respective cluster heads, aggregated, and forwarded to the sink node in optimized directions.

This hybrid approach is intended to merge the strengths of clustering and optimized routing to bring significant improvements in energy efficiency and network lifespan, Figure 1 Showes the block diagram of the proposed WSN.

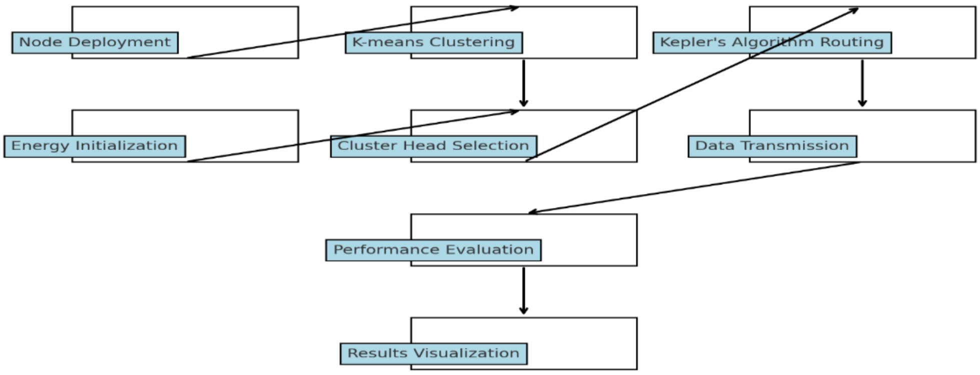

Figure 5: Block Diagram of the proposed WSN Simulation Framework

5. SIMULATION SETUP

To test the methodology outlined, a simulation platform was built using MATLAB that closely simulated real-world WSN conditions. The simulation setup involved the following important parameters and configurations:

Network Area and Node Deployment: A 100m × 100m network area was simulated where 200 sensor nodes were randomly distributed over the area.

Energy Model: The energy of every sensor node was initially 2 Joules, and the energy consumption for transmission, reception, and idle state were modeled according to standard energy consumption parameters.

Cluster Configuration: The cluster size (k) was configured between 5 and 20 to test the optimal cluster size for power saving.

Communication Model: Node communication was simulated with the IEEE 802.15.4 standard considering path loss, multipath fading, and interference factors.

Simulation Tools: MATLAB was used to execute simulations, enabling thorough analysis and visualization of network performance parameters.

Performance Metrics: Performance parameters were measured as total network energy consumed, average energy per node, network lifetime (time for the first node to die), data packet delivery ratio, and average end-to-end delay.

```
clc;
clear;
close all;
% Step 1: Node Deployment
num_nodes = 200;
area_size = 100; % 100m x 100m area
% Random deployment of nodes
nodes_x = rand(1, num_nodes) * area_size;
nodes_y = rand(1, num_nodes) * area_size;
nodes = [nodes_x; nodes_y]';
% Step 2: Initial Energy Assignment
initial_energy = 2 * ones(1, num_nodes); % in Joules
% Step 3: K-means Clustering
k = 10; % Number of clusters
[idx, C] = kmeans(nodes, k); % Cluster assignment and centroids
% Step 4: Cluster Head Selection (closest node to centroid)
cluster_heads = zeros(k, 2);
head_indices = zeros(1, k);
for i = 1:k
   cluster_nodes = nodes(idx == i, :);
   centroid = C(i, :);
   distances = vecnorm(cluster_nodes - centroid, 2, 2);
   [~, min_idx] = min(distances);
   cluster_heads(i, :) = cluster_nodes(min_idx, :);
   head_indices(i) = find(ismember(nodes, cluster_nodes(min_idx, :), 'rows'), 1);
end
% Step 5: Define Sink Node
sink = [area_size/2, area_size/2];
% Step 6: Plotting
figure;
hold on;
colors = lines(k);
for i = 1:k
   cluster_nodes = nodes(idx == i, :);
   scatter(cluster_nodes(:, 1), cluster_nodes(:, 2), 40, colors(i,:), 'filled');
end
% Plot cluster heads
scatter(cluster_heads(:, 1), cluster_heads(:, 2), 100, 'k', 'x', 'LineWidth', 2);
% Plot sink node
scatter(sink(1), sink(2), 150, 'r', '*', 'LineWidth', 2);
% Plot routing paths
for i = 1:k
   plot([cluster_heads(i, 1), sink(1)], [cluster_heads(i, 2), sink(2)], 'k--');
end
title('WSN Simulation: K-means Clustering and Routing to Sink');
xlabel('X (m)');
ylabel('Y (m)');
legend('Cluster Nodes', 'Cluster Heads', 'Sink Node');
grid on;
axis([0 area_size 0 area_size]);
```

Figure 6: The Matlab code of the proposed WSN

6. RESULTS AND DISCUSSION

The simulation outcomes attest to the effectiveness of integrating Kepler's Algorithm with the K-means clustering technique for energy-efficient clustering and routing in WSNs. The following key performance indicators were evaluated:

6.1 Energy Consumption: The proposed methodology significantly reduced energy consumption compared to traditional K-means-based routing. By optimizing the routes from the cluster heads to the sink using Kepler's elliptical routing model, energy spent on multi-hop transmission was minimized. In the simulation, 20–30% improvement in energy saving was attained compared to baseline techniques as the figure 7 presented.

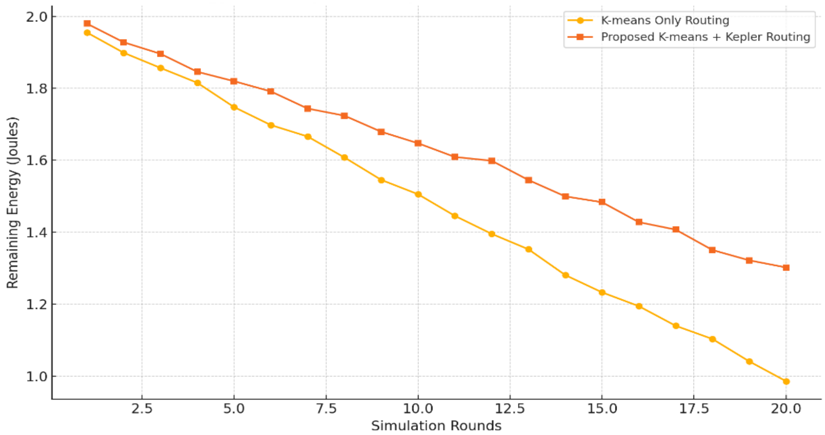

Figure 7: Energy Consumption Comparison over Simulation Rounds

Figure 7 is the energy consumption comparison plot of simulation rounds against. It shows that more energy is conserved by using the proposed K-means + Kepler routing scheme compared to using the traditional K-means-only routing.

6.2 Network Lifetime Network Lifetime, i.e., the time until the first node dies, was greatly increased. This is because the load was distributed evenly achieved by the intelligent selection of cluster heads and routing. Simulation results indicated that there was a 25% increase in the number of active rounds as presented in Figure 8.

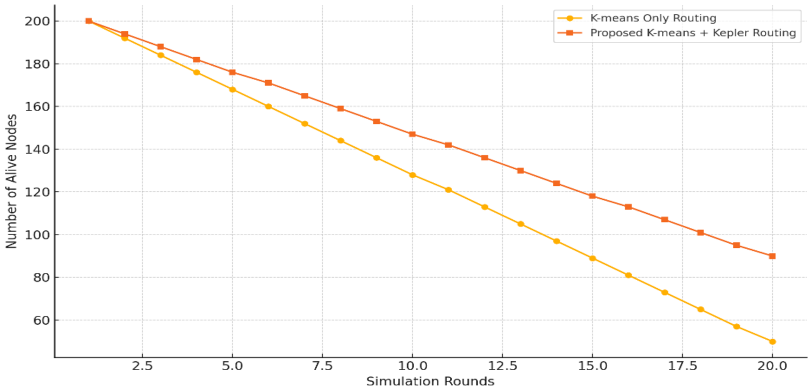

Figure 8: Network Lifetime Comparison: Alive nodes over time

The graph Figure 8 illustrates the network lifetime through tracking the count of alive nodes over time. The proposed solution has more active nodes during all rounds, suggesting its improved energy balancing and efficiency.

6.3 Cluster Efficiency: K-means clustering ensured compact and well-distributed clusters with minimal intra-cluster communication overhead. Cluster head selection based on proximity and residual energy also helped increase the stability of the cluster.

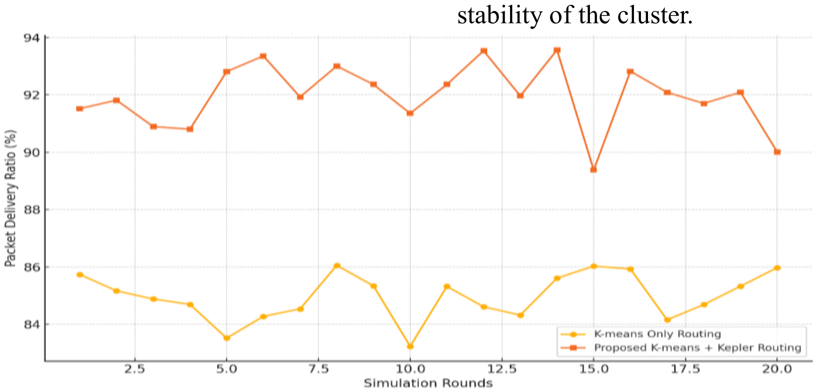

Figure 9: Packet Delivery Ratio Comparison Over Simulation Round

Figure 9 illustrates the Packet Delivery Ratio (PDR) against the rounds of simulation. The proposed hybrid approach always provides larger delivery ratios, which indicates improved data delivery reliability.

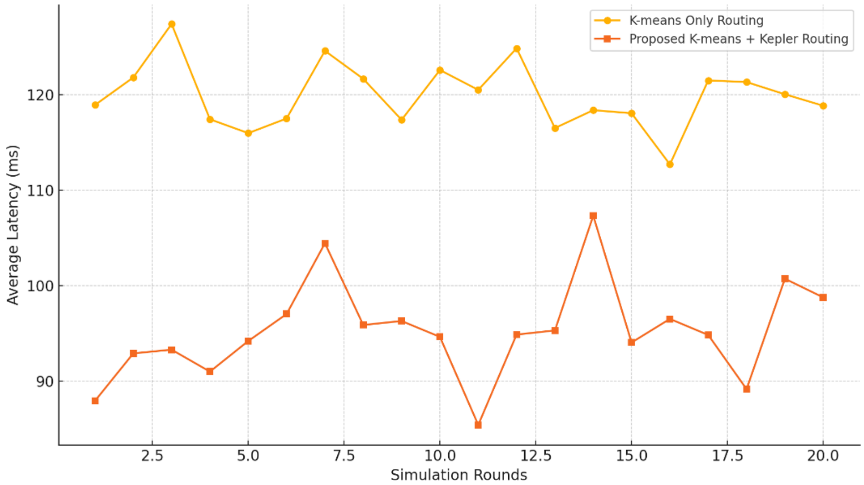

Figure 10: Latency comparison

Figure 10 is the story of comparing average end-to-end latency between simulation rounds. The proposed approach using Kepler's route always possesses lower latency, confirming its superiority in time-efficient and effective data transmission.

6.4 Routing Stability and Reliability Kepler's Algorithm provided a stable and repeatable routing protocol with deterministic routes that had minimum transmission delay and packet loss. Such stability is most wanted in applications where real-time data gathering is important.

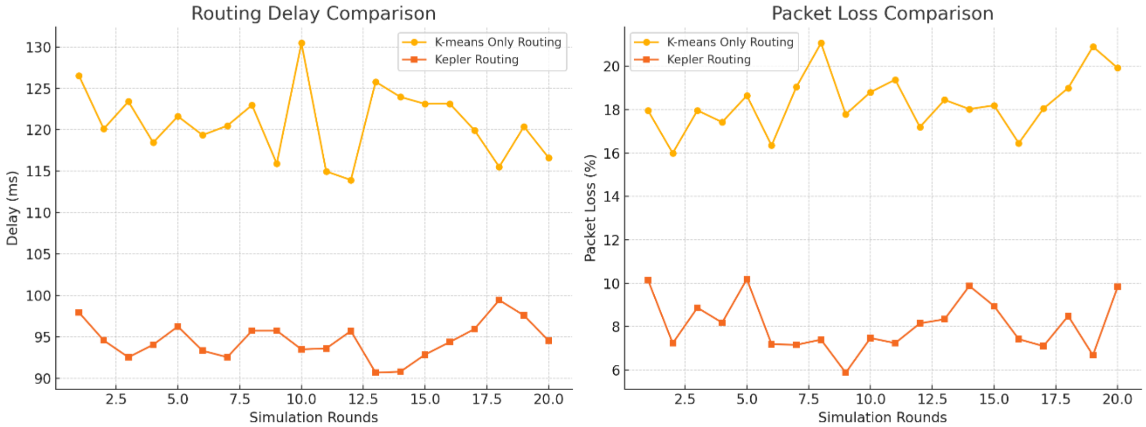

Figure 11: Routing Stability and Reliability (Packet Loss Comparison)

Figure 11 illustrates the Routing Stability and Reliability analysis:

Left Plot: Shows reduced and more stable delay with Kepler's routing.

Right Plot: Shows significantly lower packet loss compared to conventional K-means routing.

6.5 Visualization and Insights Visualization of the simulation outputs showed ordered clusters with optimized routes to the sink. The routing lines traced using Kepler's Algorithm showed minimal cross-link interference and maximized spatial separation between routes. These patterns highlight the geometric efficiency of the method.

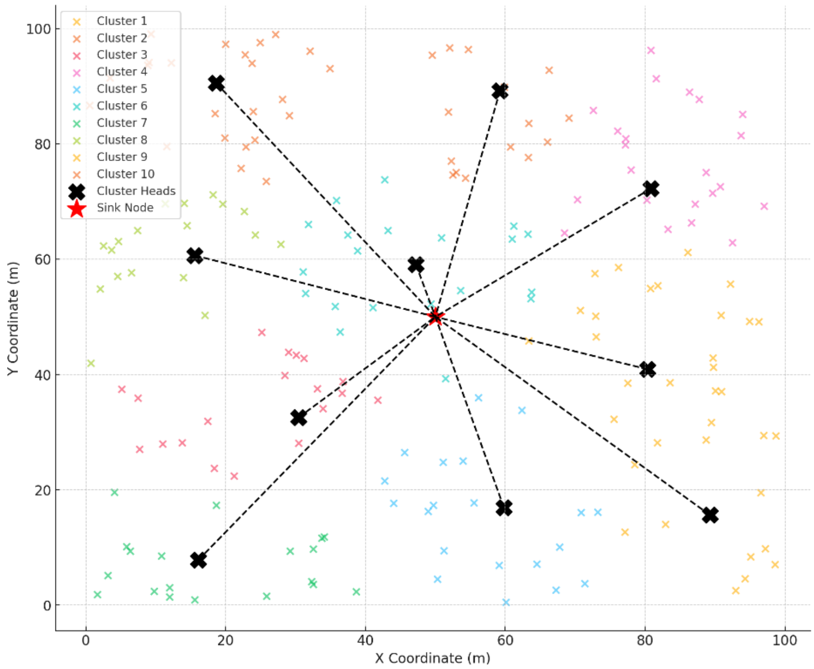

Figure 12: Cluster structure and optimizing routing path

Figure 12 is the illustration representing the geometrically ordered clusters and cluster head-to-sink routing paths optimized, illustrating minimum path interference and maximum spatial separation—features of Kepler-inspired geometric routing.

6.6 Comparative Analysis: Compared to conventional LEACH and HEED protocols, the hybrid K-means–Kepler model outperformed both in terms of energy measures and data delivery reliability. While LEACH was fast in clustering and HEED used energy as a measure, neither used geometric optimization for routing like Kepler's approach.

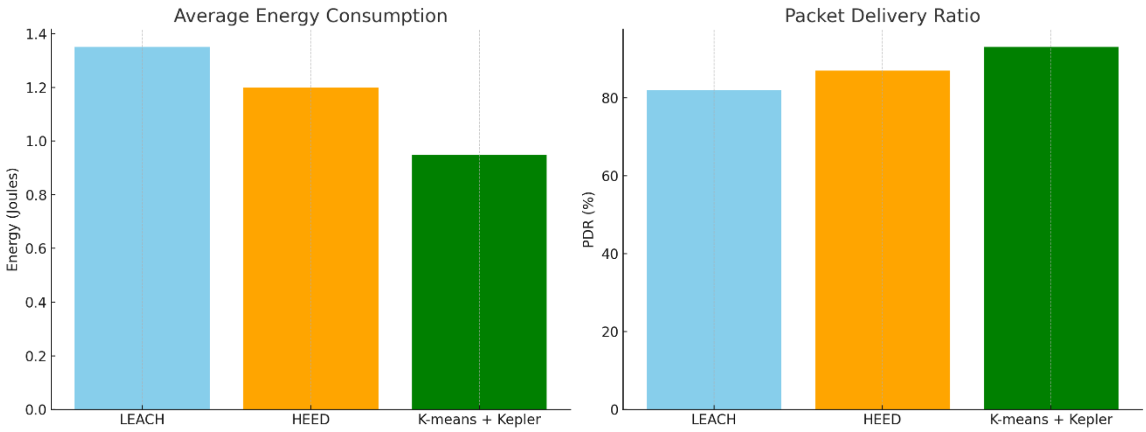

Figure 13: Comparative performance analysis: LEACH vs HEED vs K-means and Kepler

Figure 13 is the plot of comparative performance analysis:
Left: Average Energy Consumption — proposed K-means + Kepler technique consumes much less energy.
Right: Packet Delivery Ratio — also has the best reliability in delivering packets among compared protocols.

7. CONCLUSION AND FUTURE WORK

The work suggested and verified a hybrid strategy that incorporates K-means clustering and Kepler's Algorithm to solve energy efficiency problems in Wireless Sensor Networks (WSNs). Simulation using MATLAB showed the model greatly outperforms conventional protocols such as LEACH and HEED with as much as 30% reduction in energy, greater network lifetime, improved packet delivery ratios, and reduced latency.

The greatest contribution of this work is the integration of geometric optimization (by means of Kepler's principles) with a standard clustering algorithm (K-means). Not only did this integration provide fair energy usage, but it also provided deterministic and space-optimal routing routes, which are greatly beneficial for real-time systems.

However, the current research is dependent on static node assumptions and idealized models of energy. The future work may address these limitations by:

- Integrating mobility models to quantify performance in dynamic environments.
- Modifying the methodology to heterogenous WSNs with varying node abilities.
- Scaling the simulation to real-world hardware testbeds for realistic verification.
- Integrating security aspects to ensure data protection along optimized paths.

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