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Secure and Energy-Efficient Data Collection in Wireless Sensor Networks using Trust-Aware Clustering and Intelligent Mobile Sinks

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ABSTRACT: Energy consumption is one of the major factors affecting network lifetime in Wireless Sensor Networks (WSNs) and remains a critical research challenge. In existing systems, data collection is typically performed using a single mobile sink, which leads to increased energy depletion, routing inefficiencies, and reduced network lifetime. To address these issues, this work proposes a multi-mobile sink–based data collection framework combined with energy-aware and secure clustering mechanisms. In the proposed system, the sensor network is divided into clusters using the K-Means clustering algorithm, where each cluster contains a single Cluster Head (CH). The CH selection process is dynamic in nature and is enhanced using a secure Energy-LEACH++ protocol. Initially, CHs are selected randomly, while in subsequent rounds, CH selection is performed based on a composite fitness function that considers both residual energy and trust value of sensor nodes. The trust value is computed using lightweight parameters such as packet forwarding success, data consistency, and energy honesty, ensuring secure and reliable CH selection with minimal overhead. Communication between Cluster Members (CMs) and CHs follows a single-hop transmission model to reduce energy consumption. To efficiently address the problem of optimal data collection paths and avoid redundant routing, a Weighted Rendezvous Planning (WRP) strategy is employed.

KEYWORDS: Trust-aware clustering, wireless sensor networks, mobile sinks, energy efficiency, secure data collection, routing optimization, anomaly detection

I. INTRODUCTION

Wireless Sensor Networks (WSNs) consist of a large number of sensor nodes deployed over a sensing field along with mobile or static sink nodes, all equipped with power-constrained transceivers for data communication These sensor nodes are typically deployed randomly and are responsible for sensing environmental parameters and transmitting the collected data to a Base Station (BS) or sink for further processing. WSNs are widely used in applications such as environmental monitoring, civil infrastructure monitoring, healthcare, military surveillance, and industrial automation. The network lifetime of a WSN is highly dependent on the energy consumption of sensor nodes. Since sensor nodes are usually battery-powered and deployed in unattended or harsh environments, recharging or replacing batteries is often impractical. Energy consumption in WSNs primarily occurs due to sensing operations and data communication, particularly during data transmission to the BS.

To improve scalability and energy efficiency, cluster-based network architectures are widely adopted instead of flat topologies . In clustering approaches, sensor nodes are grouped into clusters, where each cluster is managed by a Cluster Head (CH). The CH collects data from its Cluster Members (CMs), performs data aggregation, and forwards the aggregated data to the BS. However, traditional clustering schemes that rely solely on energy-based CH selection are vulnerable to unreliable or compromised nodes, which may negatively affect data integrity and network performance.

II. SINGLE-HOP AND MULTI-HOP COMMUNICATION IN WSNS

Data transmission in WSNs can be performed using either single-hop or multi-hop communication model.In single-hop transmission as given in fig 1, CMs transmit sensed data directly to the CH, which reduces intra-cluster energy consumption when node density is high.

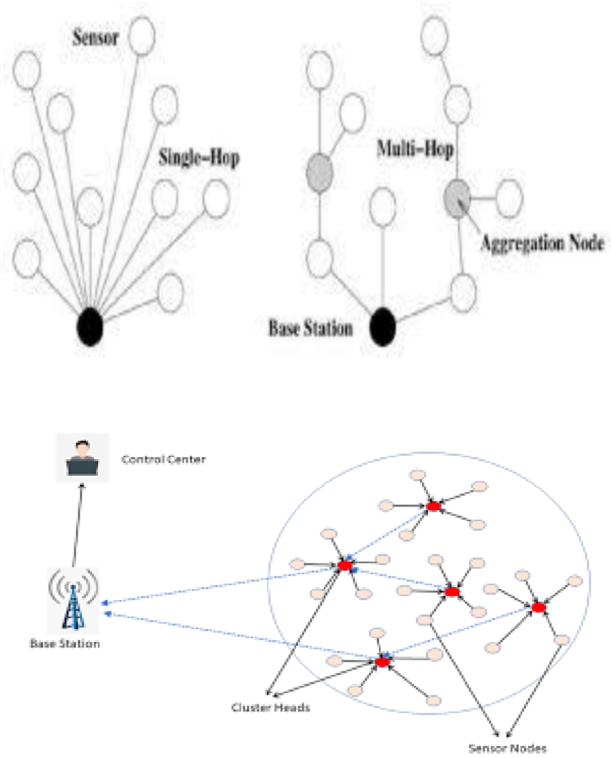

Fig. 1 Single-hop and Multi-hop routing in WSN

The main contributions of this paper are summarized as follows:

- The network is clustered using the K-Means algorithm, with a single dynamically selected CH per cluster to reduce intra-cluster energy consumption through single-hop communication.
- A secure Energy-LEACH++ protocol is proposed for CH selection by jointly considering residual energy and trust value, improving reliability and robustness.
- A multi-mobile sink architecture combined with Weighted Rendezvous Planning is employed to optimize data collection paths and reduce communication overhead.
- A reinforcement learning-based routing mechanism at the mobile sink level dynamically optimizes sink trajectories, enhancing network lifetime and energy efficiency.

2.1 MULTIPLE MOBILE SINK ROUTING IN WSN FOR ENERGY CONSERVATION

To overcome the disadvantages of the existing system, Multiple Mobile Sink is considered for gathering the data's from the Cluster Head and transmit it to the Base Station. Single Cluster Head is generated for each Cluster in random manner by using K-Means algorithm and the Cluster Member transmit the data's to the Cluster Head in Single-Hop fashion

2.2 CLUSTER FORMATION

In this module, to achieve high energy efficiency sensor nodes that are present in the network are grouped into Clusters. The main idea of clustering concept is to reduce the occurrence of network traffic from sensor node to sink and improve the energy consumption. Here the sensor nodes are located in the region in static manner. For Cluster Formation, K-Means Clustering Algorithm is considered.

III. K-MEANS ALGORITHM

The main aim of K-Means clustering algorithm partition observations into k clusters and each observation belongs to the cluster with the nearest mean value. This algorithm has a close relationship with the K-Nearest Neighbor classifier which is a popular machine learning technique. Through a certain number of Clusters it is easy to classify the given data set. The idea of K-Means is to define k centers for each cluster.

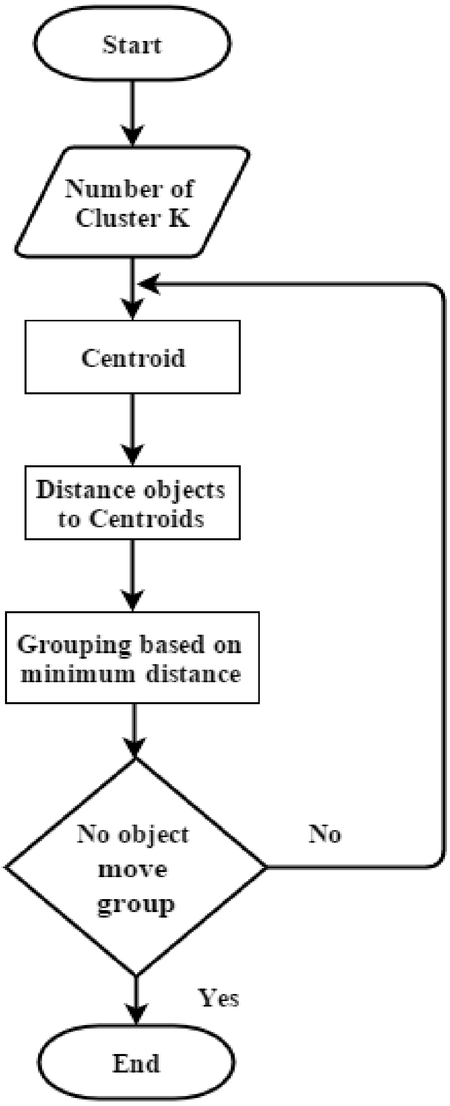

Fig.2 K-means flowchart

3.1 CLUSTER HEAD SELECTION

The CH is selected as dynamic in nature. Initially all the nodes will contain equal amount of energy. Thus the Cluster Head is identified in the network in random manner and in further rounds the nodes with highest residual energy is selected as the current CH. The Cluster Head selection is done by using Energy-LEACH algorithm.

3.2 E-LEACH ALGORITHM

E-LEACH is the enhancement of LEACH Protocol. Energy-LEACH protocol improves the cluster head selection procedure and the flowchart of E-LEACH is represented in Fig 3. The random selection of the Cluster Head is a major problem in LEACH protocol. Thus the highest energy node is considered. This protocol provides longer lifetime and save energy when compared with the LEACH protocol.

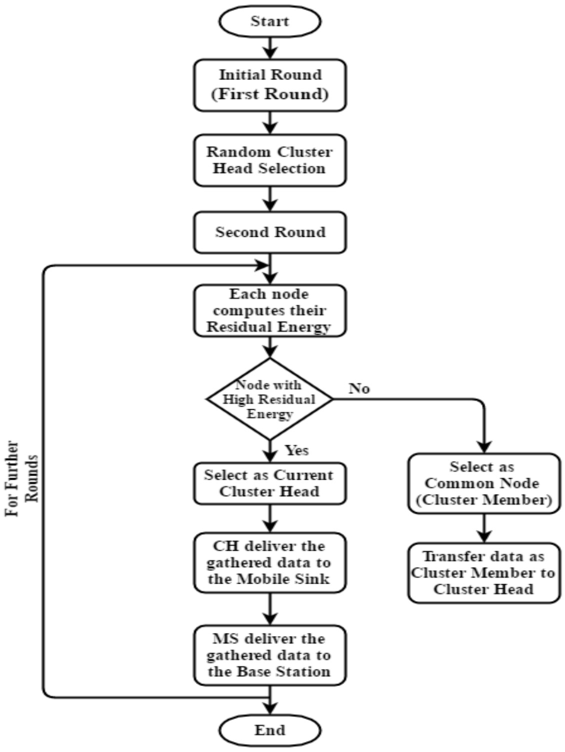

Fig.3 Energy LEACH Algorithm Flowchart

The Residual Energy of the node is calculated as,

$$RE_i(t) = \begin{cases} \left(1-\left(\frac{E_{Con}}{E_{Total}}\right)\right) * \left(\frac{K}{N-K*\left(r \bmod \frac{N}{K}\right)}\right) & if n \in G \\ 0 & Otherwise \end{cases}$$

Where E_{con} = Energy Consumed in each round,
E_{Total}= Total energy of the node,
K=Desired Percentage of the Cluster Heads for each round,
N= Total number of nodes in the network,
R=Current Round Number,
G= Set of nodes that have been Cluster Head's in the Last Rounds

IV. MOBILE SINK NODE

In the proposed system, multiple mobile sink nodes are employed to efficiently collect aggregated data from the Cluster Heads (CHs) and forward it to the Base Station (BS). These mobile sinks are assumed to be resource-rich nodes equipped with higher energy capacity, sufficient memory buffers, and powerful transceivers when compared to ordinary sensor nodes.

4.1 SPEED OF THE MOBILE SINK

The speed of the mobile sink plays a crucial role in determining packet delivery performance, energy efficiency, and overall network reliability. In regions with high sink mobility, excessive sink speed can lead to insufficient contact time between the sink and CHs, resulting in packet loss and incomplete data transfer. Conversely, very low sink speeds may increase data collection latency and buffer overflow at CHs, negatively impacting network performance.

4.2 MODELING OF MOBILE SINK SPEED VS. PACKET LOSS

Let the mobile sink move with a constant speed v(m/s) within the sensing field. When the sink enters the communication range $R$of a Cluster Head (CH), the contact time $T_c$between the sink and the CH can be approximated as:

$$T_c = \frac{2R}{v}$$

Let:

- Dbe the amount of data (bits) to be transmitted from CH to sink
- $r$be the transmission rate (bps)

The required transmission time $T_t$is:

$$T_t = \frac{D}{r}$$

For successful data transfer, the contact time must satisfy:

$$T_c \geq T_t$$

If the sink speed increases, the contact time decreases, leading to incomplete data transfer and packet loss. Packet loss probability P_{loss}can be modeled as:

$$P_{loss} = \begin{cases} 0, & \text{if } T_c \geq T_t \\ 1 - \frac{T_c}{T_t}, & \text{if } T_c < T_t \end{cases}$$

Substituting T_c:

$$P_{loss} = 1 - \frac{2Rr}{vD}$$

From this equation, it is evident that packet loss probability increases linearly with sink speed. Therefore, maintaining a controlled sink speed is essential to ensure reliable communication. In this work, the sink speed is fixed at an optimal value (10 m/s) to balance contact duration and data collection latency.

4.3 INTEGRATION WITH WRP + RL-BASED ROUTING

The proposed system integrates Weighted Rendezvous Planning (WRP) with a reinforcement learning-based sink routing mechanism to achieve adaptive and energy-efficient data collection. WRP assigns weights to Cluster Heads based on hop distance, residual energy, and cluster density, prioritizing CHs that can be reached with minimal communication cost.

Higher-weighted CHs are selected as rendezvous points for mobile sinks, reducing redundant traversal and energy consumption.

The reward function is defined to favor reduced energy consumption, minimized packet loss, and increased successful data collection:

$$Reward = \alpha \times E_{saved} + \beta \times PDR - \gamma \times P_{loss}$$

where E_{saved}represents energy savings, $PDR$is the packet delivery ratio, and $P_{loss}$is the packet loss probability.

V. TER HEAD BASED PRIORITY TRAVERSE (CHBPT)

Cluster Head Based Priority Traverse (CHBPT) is a technique initiates with the Primary Data Count (PDC) of the cluster heads present in the network. The Cluster Head maintains Primary Data Count and they are initialized to be zero. Whenever the Cluster Head encounters data entry, then the PDC value is incremented. After the Cluster Head gathers the data, a message contains Primary Data Count (PDC) value, Cluster Head position and Cluster Head identifier is sent to the Static Base Station. The Base Station maintains a prioritization table. The Cluster Heads are prioritized according to their current Primary Data Count value. Cluster Head with highest PDC value is assigned with highest priority followed by next highest PDC value.

5.1 SCHEDULING THE MOBILE SINK NODE

Scheduling the mobile sink is the process of planning how the mobile sink nodes operate. Weighted Rendezvous Planning (WRP), a heuristic method used to finds a near-optimal travelling path for the mobile sink, such that it minimizes the energy consumption of sensor nodes. WRP assigns a weight to Cluster Head (CH) based on the hop distance.

VI. RESULTS

6.1 PERFORMANCE EVALUATION

The performance evaluation demonstrates that the proposed system with dynamic Cluster Head selection and multiple mobile sinks significantly outperforms the existing approach employing dual constant Cluster Heads and a single mobile sink. Network delay, which reflects the time required for data packets to traverse from sensor nodes to the base station, is considerably reduced in the proposed scheme due to shorter communication paths, parallel data collection, and adaptive sink mobility. In addition, dynamic Cluster Head selection ensures that nodes with sufficient residual energy and favorable network conditions are selected, preventing early energy depletion and congestion.

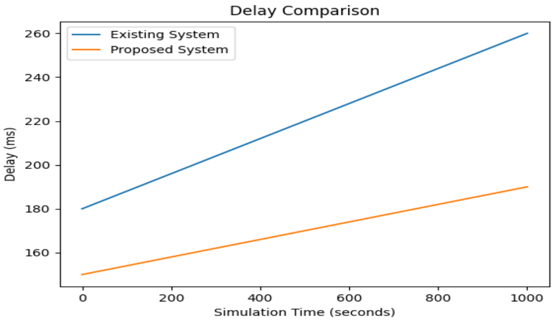

Fig. 4 Comparison of Delay

Fig 4 represents the comparison of delay for Dual Constant Cluster Head, single Mobile Sink (Existing System) and Dynamic Cluster Head selection, multiple Mobile Sinks (Proposed System). The delay of the network specifies how long it takes for a bit of data packet to travel across the network from one node to another. Time in seconds is plotted along x-axis and Delay in milliseconds is plotted along y-axis. By the usage of multiple Mobile Sinks and Dynamic Cluster Head selection, the delay gets decreased when compared with the existing system.

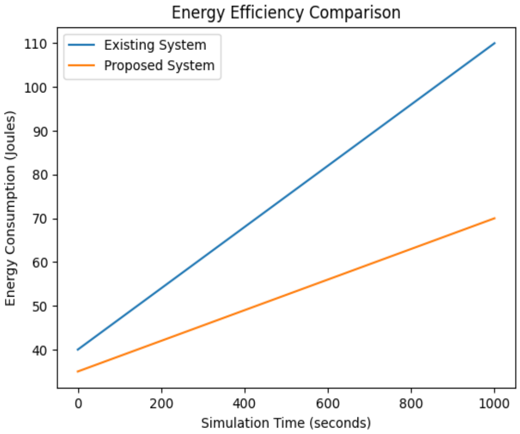

Fig. 5 Comparison of Energy Efficiency

Fig 5 represents the comparison of energy efficiency for Dual Constant Cluster Head, single Mobile Sink (Existing System) and Dynamic Cluster Head selection, multiple Mobile Sinks (Proposed System). Energy is calculated by subtracting residual energy from initial energy. Time in seconds is plotted along x-axis and energy efficiency in joules is plotted along y-axis. By the usage of multiple Mobile Sinks and Dynamic Cluster Head selection, the energy efficiency gets increased when compared with the existing system.

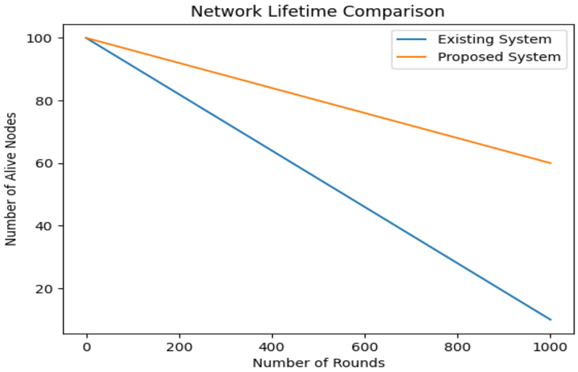

Fig. 6 Network Lifetime

Fig. 6 illustrates the comparison of network lifetime between the existing system and the proposed approach. Network lifetime is evaluated based on the number of alive sensor nodes over simulation rounds

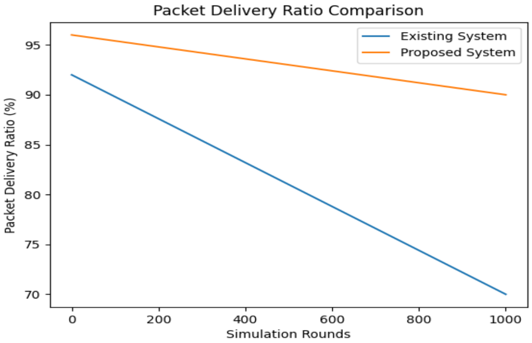

Fig. 7 Packet Delivery Ratio (PDR)

Fig. 7 shows the comparison of Packet Delivery Ratio (PDR) for both systems. The proposed system achieves a higher PDR due to reduced packet loss resulting from controlled mobile sink speed, single-hop CH-to-sink communication, and avoidance of redundant routing. In contrast, the existing system suffers from increased packet loss due to longer waiting times and congestion caused by a single mobile sink.

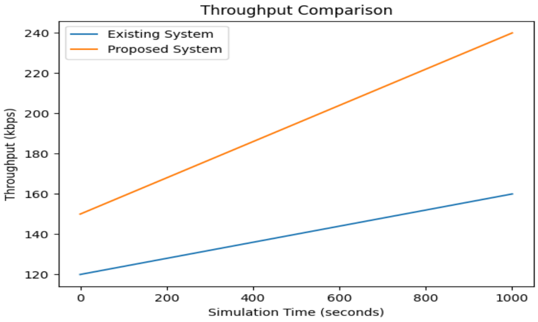

Fig. 8 Throughput

Fig. 8 presents the throughput comparison between the existing and proposed systems. Throughput represents the successful rate of data delivery to the Base Station. The proposed system achieves higher throughput due to parallel data collection by multiple mobile sinks and reduced retransmissions

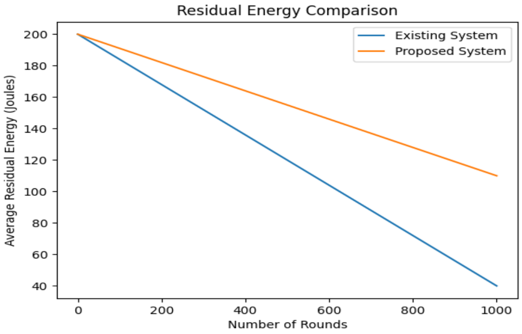

Fig. 9 Residual Energy Comparison

Fig. 9 illustrates the residual energy comparison of sensor nodes over simulation rounds. The proposed approach maintains higher residual energy due to energy-aware Cluster Head selection and reduced long-distance transmissions. The combination of multiple mobile sinks and WRP-based routing distributes communication load evenly across the network, thereby minimizing rapid energy depletion observed in the existing system.

VII.CONCLUSION

This paper presented a secure and energy-efficient data collection framework for Wireless Sensor Networks using trust-aware clustering and intelligent mobile sink routing. By integrating the proposed Energy-LEACH++ protocol, Cluster Head selection was enhanced through a combined evaluation of residual energy and node trust, ensuring reliable and secure cluster formation with minimal overhead. The use of K-Means clustering and single-hop intra-cluster communication further reduced energy consumption among sensor nodes. To overcome limitations associated with static routing and shortest-path selection, a multi-mobile sink architecture with Weighted Rendezvous Planning was employed. Additionally, a reinforcement learning-based sink routing mechanism executed at the sink level enabled adaptive and energy-aware path optimization without imposing computational burden on resource-constrained sensor nodes. Simulation results demonstrated that the proposed approach significantly improves network lifetime, reduces overall energy consumption, and enhances reliability when compared to conventional single-sink and energy-only clustering schemes. The results confirm the effectiveness of combining security, intelligence, and mobility for sustainable WSN operation.

Future research can extend this work by incorporating lightweight encryption and authentication mechanisms to further enhance data confidentiality and integrity. The integration of energy harvesting techniques, such as solar or vibration-based harvesting, can be explored to achieve sustainable and self-powered WSN deployments. Advanced multi-objective optimization techniques may be applied to jointly optimize energy consumption, delay, and packet delivery ratio. Furthermore, the proposed framework can be validated in real-world testbeds and extended to heterogeneous WSN environments with varying node capabilities and mobility patterns.

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