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A k-nearest neighbors algorithm for enhanced clustering in wireless sensor network protocols

Adil Hilmani[1], Yassine Sabri[2], Abderrahim Maizate[3], Siham Aouad[4], Fouad Ayoub[5]
[1]High School of Technology Salé, Mohammed V University, Rabat, Morocco
[2]Laboratory of Metrology and Information Processing (LMTI), Faculty of Sciences, Ibn Zohr University, Agadir, Morocco
[3]RITM, ESTC/CED-ENSEM, University Hassan II, Casablanca, Morocco
[4]Smart Systems Laboratory, National School of Computer Science and Systems Analysis, Mohamed V University, Rabat, Morocco
[5]ERATIC Team, LaREAMI Lab, CRMEF-K Kenitra, Morocco

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ABSTRACT

Wireless sensor networks (WSNs) are small, autonomous, battery-powered nodes capable of sensing, storing, and processing data, while communicating wirelessly with a central base station (BS). Optimizing energy consumption is a major challenge to extend the lifetime of these networks. In this study, we propose an innovative approach combining the k-nearest neighbors (KNN) algorithm with hierarchical and flat routing protocols to improve node selection and clustering in three key protocols: low-energy adaptive clustering hierarchy (LEACH), threshold-sensitive energy efficient sensor network protocol (TEEN), and hybrid energy-efficient distributed clustering (HEED). Concretely, KNN is used to rank nodes based on their spatial and energy proximity, thus optimizing the choice of cluster heads (CHs) and reducing long and costly connections. Simulations show a reduction in the inter-CH distance, a decrease in overall energy consumption, and an extension of the network lifetime compared to conventional versions of the protocols. These improvements not only help increase operational efficiency, but also enhance communications stability and security, providing a robust and sustainable solution for critical WSN applications.

Corresponding Author:

Adil Hilmani
High School of Technology Salé, Mohammed V University
Rabat, Morocco
Email: adilhilmani@gmail.com

1. INTRODUCTION

Wireless sensor networks (WSNs) play a vital role in various applications, such as environmental monitoring, healthcare, and industrial process optimization. These networks connect sensors that collect data and transmit it to a central station. However, energy management remains a major challenge, as these sensors operate on batteries with limited autonomy. Despite extensive research aimed at reducing energy consumption, particularly through sensor clustering and data routing optimization, the performance and durability of WSNs remain improvable [1]-[4].

The main challenge is to reconcile energy efficiency and data transmission reliability. Traditional clustering approaches do not always allow for a balanced distribution of the energy load between nodes, which accelerates their failure and compromises the overall operation of the network. It is therefore essential to explore new solutions to improve the robustness and longevity of WSNs [5]-[10].

In this context, this research proposes an innovative integration of the k-nearest neighbors (KNN) machine learning technique with the low-energy adaptive clustering hierarchy (LEACH), hybrid energy-efficient distributed clustering (HEED), and threshold-sensitive energy efficient sensor network protocol (TEEN) clustering protocols to optimize the choice of cluster head (CHs) based on criteria remaining energy, mean distance to neighboring nodes, and local density. This approach reduces energy consumption through better load distribution among nodes, extends network lifetime by limiting long and energy-consuming transmissions, and improves data transmission reliability by reducing the average distance between nodes and their CHs. The performance of the proposed system is validated by network simulator 2 (NS2) simulations, accompanied by statistical analyses and a sensitivity study that demonstrate the robustness and superiority of this approach over traditional methods.

The remainder of this paper is organized as follows: section 2 reviews related work. Section 3 presents an overview of the proposed system. Section 4 details the characteristics and components of the proposed protocol. Section 5 describes its simulation and evaluates its effectiveness. Finally, section 6 concludes the paper.

2. RELATED WORKS

Many researchers have studied energy reduction in WSNs, leading to the development of various routing protocols. These protocols are generally classified into four categories: hierarchical, data-centric, location-based, and network flow-based [11], [12]. This paper focuses on hierarchical protocols, which aim to optimize data routing to the base station (BS) while improving energy efficiency. Among these protocols, LEACH [13], TEEN [9], and HEED [14] adjust CH selection based on node energy levels and network characteristics.

The KNN algorithm has been integrated into some protocols to optimize CH selection and extend network lifetime. For example, its application to the TEEN protocol has enabled better energy management through more efficient CH selection [15]. Other approaches have combined KNN with metaheuristic algorithms to improve node placement, although this leads to increased computational complexity and more complex dead node management [16].

Beyond energy optimization, the KNN algorithm has also been exploited for WSN security, particularly in intrusion detection [17]. Some studies have implemented hybrid models combining KNN and other machine learning techniques to enhance cybersecurity and reduce network vulnerabilities [18].

Furthermore, advanced approaches have been proposed to simultaneously improve the security and energy efficiency of WSNs. The HMRP-IWSN, which combines deep neural networks with an energy-efficient routing protocol, has demonstrated a significant improvement in overall network performance [19].

Multi-objective optimization has also been studied to balance multiple criteria such as energy efficiency, latency, and transmission reliability [20], [12]. Finally, machine learning techniques such as support vector machines (SVM) have been applied to improve CH selection and optimize energy management of WSNs [21]. These advances show that artificial intelligence plays a key role in improving WSNs, opening the way to new perspectives in optimization and security.

3. DESCRIPTION OF THE SYSTEM

A complete description of the model of our proposed system will be presented in this section. The network model will be presented first, then the energy consumption model, before defining the key concepts and assumptions underlying this study.

3.1. Network model

The proposed protocol targets non-dynamic networks composed of a BS and n static sensor nodes. The WSN is deployed on an x and y plane. Static BS collects data from n randomly distributed sensor nodes that are responsible for sensing and information collection.

For network simulation, all sensors have the same technical characteristics (same energy levels, same processing and communication capabilities). All nodes know their position and can control their energy in order to aggregate data as much as CH. The BS is assumed to have unlimited computing power and resources, allowing direct communication with all nodes.

3.2. Model of energy consumption

The proposed algorithm uses a similar energy consumption approach to LEACH [22]-[25]. It differentiates two communication scenarios based on the distance between nodes. When the distance to be transmitted is beyond the threshold d_0, the model takes into account signal reflection and scattering effects. Conversely, for distances less than d_0, a free-space, obstacle-free environment is assumed [26], [27]. The threshold is calculated using (1).

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \tag{1}$$

where ε_{fs} and ε_{mp} denote the amplification factors of the model in both cases according to threshold d_0. E_{tx} is the energy consumed during the transmission of m bits in a path d:

$$E_{tx} = \begin{cases} mE_{elec} + m\varepsilon_{fs}d^2, d < d_0 \\ mE_{elec} + m\varepsilon_{mp}d^4, d \geq d_0 \end{cases} \tag{2}$$

where E_{elec} is the energy consumed to send or receive a bit.
In (3) represents the reception energy of m bits it is the energy consumed.

$$E_{rx} = mE_{elec} \tag{3}$$

4. PROPOSED PROTOCOL

The protocol we propose is structured into three primary steps: i) clustering process, ii) CH election, and iii) data collection and communication. These steps collectively improve the network transmission efficiency by utilizing clustering, reducing energy dissipation and consolidating data to prepare it for sending. The collected information is finally transmitted to the BS via optimized intra-cluster and inter-cluster communication paths.

4.1. Clustering process

Clustering is a critical step for optimizing energy consumption in WSNs. This step involves grouping network nodes into clusters using the KNN algorithm. The clustering process involves several key steps, including distance calculation, KNN selection, cluster initialization, and node assignment to clusters, which will be detailed below.

The first step is to measure the distance between each node and the other nodes in the network. The distance between two nodes v_i and v_j, with their respective positions $P_i = (x_i, y_i)$ and $P_j = (x_j, y_j)$. The distance between two nodes v_i and v_j is given by (4):

$$d(i,j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{4}$$

Once the distances between all nodes are calculated, each node selects its K KNN. Each node v_i must first calculate the cost function $Cost\ (i,j)$ for each other node v_j in the network, where $j \neq i$. This cost function takes into account as criteria the distance between nodes and the remaining energy. Once the costs are calculated, the node v_i sorts these values in ascending order. Then, it selects the K nodes v_i having the K-lowest costs.

$$N_i = \{v_j\ ,\ v_j \neq v_i\ , Cost(i,j)\ is\ among\ the\ K\ smallest\ values\} \tag{5}$$

$$Cost\ (i,j) = \exp\big(d(i,j)\big) + \exp(|E_i - E_j|) \tag{6}$$

where N_i represents the set of KNN of v_i, $d(i,j)$ is the distance between nodes v_i and v_j, E_i and E_j are the energies of the nodes v_i and v_j.

Once each node has calculated its KNN, the next phase is to initialize the clusters. The idea is to randomly choose K nodes as cluster centers. These nodes will be the representative nodes or centroids of their respective clusters. The choice of cluster centers is essential for the proper functioning of the algorithm.

Once the cluster centers are initialized, it is necessary to assign each node v_i to the cluster whose center is closest. This assignment is done using the distance between each node and the cluster centers. Node v_i is assigned to cluster k for which the distance d is minimal (7).

$$C(i) = \arg min_k\ d(i, C_k) \tag{7}$$

where $C(i)$ is the cluster to which node v_i is assigned and C_k is the center of the cluster k.

After the initial assignment of nodes to clusters based on the proximity of the centers, the clusters may not be optimal. To address this issue, the process of assigning nodes and updating centers is iterated. At each iteration, the centers of the clusters are recalculated by taking the average of the positions of the nodes assigned to them (8).

$$C_k = \left(\frac{1}{|C_k|}\sum_{v_j \in C_k} x_j, \frac{1}{|C_k|}\sum_{v_j \in C_k} y_j\right) \quad (8)$$

where C_k is the center of the cluster k, $|C_k|$ indicates how many nodes are in the cluster k, and (x_j, y_j) are position of the node de v_i in the cluster C_k. The cluster update process (reassigning nodes and recalculating centers) is repeated until the clusters no longer change, i.e., nodes no longer change clusters in the next iteration. This stabilization criterion ensures that the clustering is optimal.

4.2. The cluster head election

To optimize power consumption in WSNs, our paper proposes an efficient method for selecting CHs. The selection process is based on three key criteria: the node's energy reserve, its spatial centrality within the cluster, and its communication load. These factors are combined into a fitness function, which computes a score for each node, as defined in (9):

$$CH_{score(i)} = \frac{E_i}{E_{max}} + S_i - L_i \quad (9)$$

where E_i is the energy reserve of node i and E_{max} is the starting energy (used for normalization). S_i represents the spatial centrality of node iii within its cluster and is calculated as (10):

$$S_i = -\frac{1}{|C_K|}\sum_{j \in C_K} d(i,j) \quad (10)$$

where C_K is the set of nodes in cluster K, $d(i,j)$ is the distance between node i and node j, and $|C_K|$ is the total number of nodes in the cluster. The communication load L_i is defined as the number of nodes with which i communicates, given by (11):

$$L_i = \sum_{j \in C_K, j \neq i} \mathbb{I}(d(i,j) \leq r_{comm}) \quad (11)$$

where r_{comm} is the communication range threshold, and $\mathbb{I}(\,)$ is an indicator function that equals 1 if j is within the communication range of i, and 0 otherwise.

After calculating the fitness scores for all nodes within a cluster, the node with the highest score is chosen as the CH:

$$CH_K = \arg min_{i \in C_K} CH\_score(i) \quad (12)$$

This approach enables dynamic selection of CHs based primarily on energy reserve, which enhances energy management and prolongs the network's operational lifetime.

4.3. Data collection and communication

Our paper presents an optimized method for data aggregation and transmission in clustered WSNs to enhance energy efficiency and network longevity. The proposed method employs a multi-hop communication strategy where CHs relay data to the BS while considering key factors such as residual energy, the number of neighbors, communication load, and link quality. The link quality factor LQF_{ij} between two CHs i and j is computed as (13):

$$LQF_{ij} = \frac{1}{1 + P_{loss,ij}} \times \frac{SNR_{ij}}{SNR_{th}} \quad (13)$$

where $P_{loss,ij}$ is the packet loss probability between CH i and j, SNR_{ij} is the signal-to-noise ratio of the link, and SNR_{th} is a predefined threshold for reliable communication. A higher LQF_{ij} indicates a better-quality link.

To determine the best relay node, a cost function is computed for each neighboring CH, integrating residual energy, the number of neighbors, the link quality, and distance to the BS (14).

$$C_{ij} = \frac{1}{E_j} + \frac{1}{N_j} + d(j, BS) - LQF_{ij} \quad (14)$$

Instead of always choosing the CH with the lowest cost, we introduce a probability-based relay selection to distribute network traffic more efficiently:

$$P_{ij} = \frac{e^{-\mu C_{ij}}}{\sum_{k\epsilon\mathbb{N}_i} e^{-\mu C_{ik}}} \tag{15}$$

where μ adjusts the trade-off between deterministic and probabilistic selection, and $\mathbb{N}_i$ is the set of neighboring CHs.

Finally, the CH selects its next relay node based on (16).

$$Relay_i = \arg min_{j\in\mathbb{N}_i}\ C_{ij} \tag{16}$$

This approach ensures that multi-hop transmission dynamically prioritizes CHs with higher energy, better connectivity, and lower congestion, leading to improved energy balance and extended network lifetime.

5. SIMULATION AND DISCUSSION

In this section, we present and compare the simulation results of the original LEACH, TEEN, and HEED algorithms alongside their enhanced versions developed using our proposed KNN-based protocol. Table 1 summarizes the common parameters applied in both sets of simulations.

Table 1. Simulation parameter

Parameter	Value
Network area	200×200
Number of nodes	400
Maximum number of rounds	5000
Probability for a node to be elected as CH	0.1
BS location	200×200
Energy dissipation per bit E_{elec}	50 nJ/bit
Energy dissipation for free space $\mathcal{E}_{fs}$	10 pJ/bit/m^2
Energy dissipation for multipath delay $\mathcal{E}_{mp}$	0.0013 pJ/bit/m^2
Energy dissipation per bit E_{rx}	50 nJ/bit
Data packet size	500 bytes
Simulation time	600 s

Figure 1 displays the outcomes for the enhanced protocols LEACH-KNN, TEEN-KNN, and HEED-KNN. When compared to their original counterparts, these improved versions demonstrate superior clustering efficiency. The CHs are positioned closer to the BS, which reduces communication overhead. Furthermore, the network maintains stable operation without any CHs failing, and importantly, all CHs are located away from the network boundaries, ensuring balanced coverage.

Figures 2 and 3 illustrate the simulation outcomes of our KNN-based protocol, highlighting its clear advantages over the traditional LEACH, TEEN, and HEED protocols. By accurately determining the optimal number of clusters and selecting CHs based on specific node attributes and their spatial positions, the protocol achieves improved resource utilization. These enhancements lead to reduced energy consumption, increased network longevity, and a more balanced energy distribution among nodes.

Figure 2 compares the total energy consumption of sensor nodes under both the original and the proposed methods. The results reveal that our approach significantly lowers energy usage, primarily due to the refined cluster count and more strategic CH selection, which collectively foster more effective energy management throughout the network.

In Figure 3(a), the packet delivery ratio is notably higher with the proposed protocol, even as the node density increases. This contrasts with the original protocols, where packet delivery tends to degrade under heavier network loads. Our method thus ensures not only energy efficiency but also robust and reliable data transmission, underscoring the critical role of optimized CH assignment and cluster structure in enhancing overall network performance.

From Figure 3(b), the modified protocol approach ensures better stability and increased network longevity even in the presence of high node density, unlike the original approach. This version not only optimizes energy consumption but also helps maintain a more robust network in the long run, thus ensuring a longer lifetime.

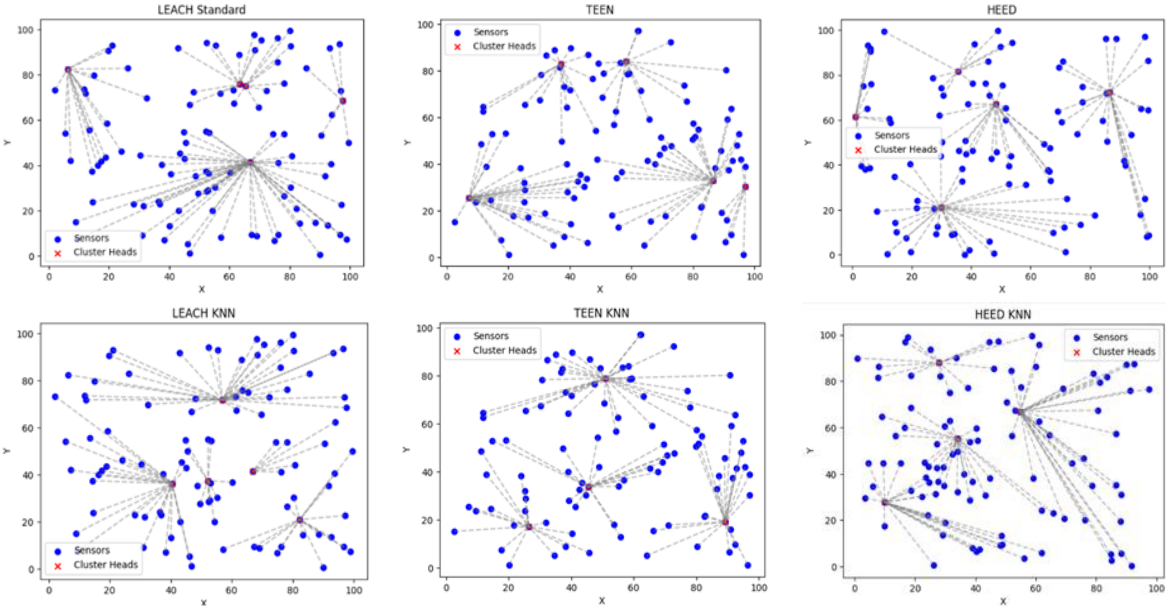


Figure 1. Results of implementing: LEACH-KNN, TEEN-KNN, and HEED-KNN

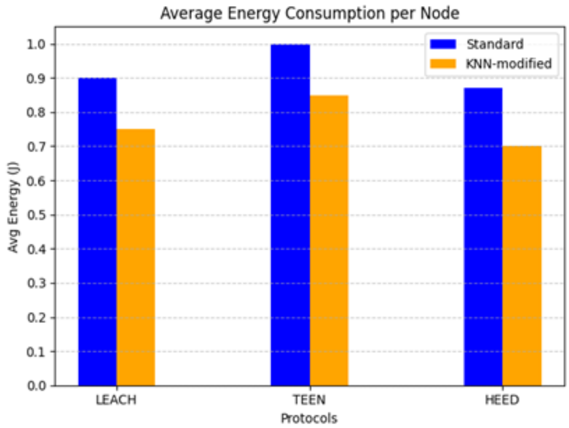
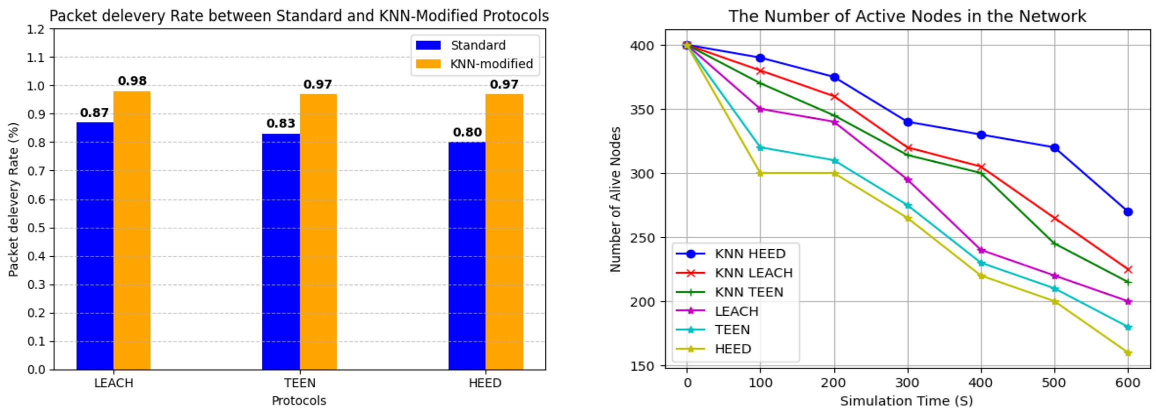


Figure 2. Average energy consumption per node in the original and KNN-modified protocols



(a) (b)

Figure 3. Performance metrics of (a) packet delivery rate and (b) number of alive nodes

Simulation results confirm that our proposed approach based on modified KNN of LEACH, TEEN and HEED protocols outperforms the original versions in terms of energy efficiency, network stability and resource distribution. By optimizing the number of clusters and improving CH selection, the proposed approach significantly reduces energy consumption and improves network reliability. The obtained results demonstrate that the modified KNN protocol maintains higher packet delivery rates, ensures better stability and extends network lifetime even in high-density environments. These improvements highlight the effectiveness of our approach in achieving efficient energy management and reliable data transmission.

6. CONCLUSION

This paper proposes a novel approach to enhance WSN protocols using the KNN algorithm. By addressing the limitations of LEACH, HEED, and TEEN protocols, particularly the lack of visibility on dead nodes and CHs, KNN helps create more efficient clusters, improving energy consumption and network stability. The approach ensures that dead CHs are excluded, optimizing CH selection based on residual energy and BS proximity, which reduces communication delays. Results show improved energy efficiency and fewer dead nodes. While the KNN algorithm significantly improves WSN performance, it is important to note that higher node density can lead to increased computational complexity, and network scalability may be limited in highly dynamic environments requiring constant cluster adaptation. Future work will explore real-world implementations and dynamic topologies for further optimization.

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BIOGRAPHIES OF AUTHORS

Adil Hilmani received his diploma as much as a Network and Telecommunication engineer from the superior engineering school, from the University of Seville in Spain. In 2021, he had his doctorate in computer engineering at the National School of Electricity and Mechanics (ENSEM) in Casablanca-Morocco. Currently, he is a professor of High School of Technology Salé, Mohammed V University, Rabat, Morocco. He can be contacted at email: adilhilmani@gmail.com.

Yassine Sabri Born on October 28th, 1984, in Rabat, Morocco, he received a B.Sc. in science and technology and mathematics from Mohamed 5 University of Rabat in 2006 and an M.Sc. in Engineering from the University Chouaib Douakaly in 2008. He earned his Ph.D. in WSN technology at the Laboratory of Science and Technology. He can be contacted at email: sabriyassino@gmail.com.

Abderrahim Maizate after completing his diploma in Network and Telecommunication engineering from the University of Seville in Spain, he went on to obtain his doctorate in computer. He is a member of IEEE. He can be contacted at email: maizate@hotmail.com.

Siham Aouad born in Tangier, Morocco in 1981, holds a Ph.D. in Computer Engineering from Mohammadia School of Engineers EMI in 2014. Currently, she works, SDN, AI, virtualization, cloud computing, and security. She can be contacted at email: siham.aouad@ensias.um5.ac.ma.

Fouad Ayoub born in Kenitra, Morocco, in 1979. He obtained his B.Sc. degree in Mathematical Sciences in September 1998. He then pursued his graduate studies at Mohammed V University, Faculty of Sciences, Rabat, Morocco, where he earned his Master of Science and Ph.D. degrees in Engineering, Telecommunications, and Multimedia in 2005 and 2011, respectively. He can be contacted at email: ayoubfouadn@gmail.com.