

# Energy-efficient clustering optimization for heterogeneous wireless sensor networks with K-nearest neighbors algorithm

Adil Hilmani<sup>1</sup>, Yassine Sabri<sup>2</sup>, Abderrahim Maizate<sup>3</sup>, Siham Aouad<sup>4</sup>, Fouad Ayoub<sup>5</sup>

<sup>1</sup>Laboratory for System Analysis, Information Processing, and Integrated Management (LASTIMI), High School of Technology Salé, Mohammed V University, Rabat, Morocco

<sup>2</sup>Laboratory of Metrology and Information Processing (LMTI), Faculty of Sciences, Ibn Zohr University, Agadir, Morocco

<sup>3</sup>Research and Innovation Technology Management (RITM), ESTC/CED-ENSEM, University Hassan II, Casablanca, Morocco

<sup>4</sup>Smart Systems Laboratory, National School of Computer Science and Systems Analysis, Mohamed V University, Rabat, Morocco

<sup>5</sup>Equipe de Recherche appliquée en technologies de l'information et de la communication Team, Laboratoire de Recherche en Enseignement, Apprentissage, Mathématiques et Informatique, Regional Center for Education and Training Professions, Kenitra, Morocco

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## ABSTRACT

Wireless sensor networks (WSNs) consist of autonomous sensing nodes whose operation relies on limited energy resources. To extend the operational lifetime of such systems, optimizing power consumption is essential. Clustering plays a key role in enhancing network stability and improving communication efficiency. This work proposes an improved clustering strategy based on the K-nearest neighbors (KNN) algorithm to reduce transmission distances in heterogeneous networks. By integrating this approach into hierarchical protocols such as Department of Electrical and Electronic Engineering (DEEC), Electrical Engineering Center (EEC), Center for Advanced Materials and Processes (CAMP), the method refines both node selection and cluster organization. Simulation results obtained using network simulator 2 (NS2) demonstrate that the modified protocols significantly reduce energy dissipation while increasing overall network lifetime. This combined approach improves system efficiency and provides a robust solution for sustainable energy management in WSNs, meeting the requirements of highly demanding applications.

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## Corresponding Author:

Adil Hilmani

Laboratory for System Analysis, Information Processing, and Integrated Management (LASTIMI)

High School of Technology Salé, Mohammed V University

Rabat, Morocco

Email: [adilhilmani@gmail.com](mailto:adilhilmani@gmail.com)

## 1. INTRODUCTION

The use of wireless sensor networks (WSNs) has become widespread in strategic sectors such as industrial automation, healthcare, and environmental monitoring. These infrastructures rely on autonomous sensing units that transmit data to a centralized base station (BS) node. Energy preservation remains a major technical challenge, as the operational lifetime of these networks is strictly constrained by limited battery resources. Despite advances in routing and clustering optimization, improving the durability of these systems remains a major research focus.

The critical point for these networks is to guarantee constant data transmission without prematurely depleting energy resources. Conventional clustering techniques often exhibit weaknesses in load distribution between nodes, leading to localized failures that compromise the overall integrity of the network. To overcome these shortcomings, it is imperative to develop more balanced partitioning strategies [1]–[4].

This scientific contribution proposes integrating artificial intelligence, via the K-nearest neighbors (KNN) algorithm, into communication protocols for WSNs. By adapting the Department of Electrical and Electronic Engineering (DEEC), Electrical Engineering Center (EEC), Center for Advanced Materials and Processes (CAMP) models, we introduce optimized versions (DEEC-KNN, EEC-KNN, and CAMP-KNN) that refine the selection of cluster heads (CH). These distributed models aim to reduce communication distances and maximize the network's operational lifetime [5]–[10].

The organization of this article is as follows: section 2 reviews related research, while section 3 details the proposed system architecture. Section 4 presents the technical specifications of our protocol, followed by section 5, which analyzes the performance obtained through simulation. Finally, section 6 concludes the study by outlining future research directions.

## 2. RELATED WORKS

The energy efficiency problem in WSNs has motivated the development of multiple routing strategy families, such as hierarchical, data-driven, location-aware, and flow-optimized approaches. Each category aims to improve communication efficiency while reducing energy consumption and extending network lifetime. This study specifically investigates hierarchical routing protocols, including DEEC, EEC, and CAMP, which are designed to optimize energy usage through structured clustering mechanisms. These models optimize cluster leader selection based on node residual energy and the overall network state. Their primary objective is to extend network lifetime while maintaining efficient communication [11]–[15].

The KNN algorithm has also been used in WSNs to improve CH selection and energy management, including in threshold-sensitive energy-efficient network (TEEN)-based approaches [16], hybrid models with metaheuristics [17], intrusion detection systems [18], [19], and combined deep learning frameworks [20]. Other studies have explored multi-objective optimization and machine learning methods such as SVM to enhance energy efficiency and network performance [21]–[23].

However, most existing approaches optimize a single criterion or depend on specific protocols and rarely consider jointly residual energy, node centrality, communication load, and transmission quality. In contrast, our approach uses a multi-criteria KNN model to optimize these factors simultaneously, reducing energy consumption, communication overhead, and transmission cost while improving network stability and lifetime.

## 3. SYSTEM OVERVIEW

This section describes the system model used in this study. It first presents the network architecture, then the adopted energy dissipation model. Finally, the main assumptions and definitions necessary for understanding the proposed approach are outlined.

### 3.1. Network model

Our algorithm considers a static WSN composed of a BS and  $n$  fixed sensor nodes randomly deployed over a two-dimensional (2D) area. Nodes remain stationary after deployment and are homogeneous, sharing the same initial energy and similar communication and processing capabilities. Each node is aware of its location, residual energy, and role in cluster formation. The BS has unlimited energy and computational power and can directly communicate with all sensor nodes for data collection.

### 3.2. Energy consumption analysis mode

This study adopts the low-energy adaptive clustering hierarchy (LEACH) reference energy model for WSNs to evaluate energy dissipation [24]–[27]. This model considers two cases based on the transmission distance between nodes. When the distance is below the critical threshold  $d_0$ , the free-space propagation model is applied, assuming a clear and unobstructed communication channel. Above this threshold, the multipath model is applied to account for propagation effects such as reflection and diffraction. The threshold is defined by:

$$d_0 = \sqrt{\frac{\mathcal{E}_{fs}}{\mathcal{E}_{mp}}} \quad (1)$$

In this expression,  $\mathcal{E}_{fs}$  and  $\mathcal{E}_{mp}$  respectively denote the amplification coefficients related to the free-space and multipath propagation models. The total transmission energy  $E_{tx}$  required by a node to transmit a packet of  $(m)$  bits to a destination located at a distance  $d$  is described by (2).

$$E_{tx} = \begin{cases} mE_{elec} + m\epsilon_{fs}d^2, & d < d_0 \\ mE_{elec} + m\epsilon_{mp}d^4, & d \geq d_0 \end{cases} \quad (2)$$

Here,  $E_{elec}$  represents the energy consumed by the onboard electronic circuits for processing each bit, whether during transmission or reception. Unlike transmission, the reception energy  $E_{rx}$  for a message of  $m$  bits is considered to be proportional to its size and independent of the distance  $d$ , as shown in (3).

$$E_{rx} = mE_{elec} \quad (3)$$

#### 4. PROTOCOL PROPOSED

The proposed protocol is based on three main steps: cluster formation, CH selection, and data grouping with transmission. This structure improves communication efficiency by organizing nodes into clusters, reducing energy consumption, and aggregating data before sending it. The final transmission to the BS is performed through optimized intra- and inter-cluster routing paths, ensuring reliable data delivery [28], [29].

##### 4.1. The cluster formation

Cluster formation is a crucial step in optimizing the energy efficiency of WSNs. In this phase, the goal is to group the nodes of the network into clusters using the KNN algorithm. Cluster formation involves several key steps that are detailed below. We will focus on calculating distances, selecting the KNN, initializing the clusters, and assigning nodes to clusters.

The procedure begins by measuring the spatial distance between each node and its neighboring nodes within the network infrastructure. For two nodes  $v_i$  and  $v_j$ , located at positions  $P_i = (x_i, y_i)$  and  $P_j = (x_j, y_j)$  respectively, this distance is computed using the standard Euclidean formula (4).

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

Once these measurements are obtained, each node  $v_j$  evaluates a cost function  $Cost(i, j)$  for all other nodes  $v_j$  where  $j \neq i$ . This hybrid metric simultaneously considers geographical proximity and the remaining energy levels. The resulting values are then sorted in ascending order, allowing node  $v_j$  to select the KNNs with the lowest cost values (5) and (6).

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

$$Cost(i, j) = \exp\left(\frac{d(i, j)}{\sigma_d}\right) + \exp\left(\frac{|E_i - E_j|}{\sigma_E}\right) \quad (6)$$

In these expressions,  $E_i$  and  $E_j$  denote the respective energy levels, while  $\sigma_d$  and  $\sigma_E$  are scaling parameters. After identifying the neighbors, the system initializes the clusters by randomly selecting  $K$  nodes to act as initial cluster centers (centroids).

To improve network stability and balance the workload, cluster centers are not computed using a simple arithmetic mean but through an energy-weighted formulation. This ensures that nodes with higher residual energy have a stronger influence on the centroid position. The weighted center of a cluster  $C_k$  is then defined by (7).

$$C_k = \frac{\sum_{v_i \in C_k} E_i(x_i, y_i)}{\sum_{v_j \in C_k} E_j} \quad (7)$$

This strategy favors positioning CHs near nodes with higher energy reserves. As a result, it reduces the risk of early battery depletion, thereby extending the overall operational lifetime of the system.

##### 4.2. The cluster head selection

The CH selection phase is a critical step for ensuring network sustainability. The proposed method relies on a multi-criteria evaluation to identify the most suitable nodes for this role. It uses a fitness function that combines three key factors: residual energy, spatial centrality within the cluster, and communication load. For each node  $i$  a score is computed according to (8):

$$CH_{score(i)} = \frac{E_i}{E_{max}} + S_i - L_i \quad (8)$$

where  $E_i$  is the residual energy of node  $i$  and  $E_{max}$  is the initial energy of the node (used for normalization).  $S_i$  represents the spatial centrality of node  $i$  within its cluster and is calculated as follows:

In this model, the ratio  $\frac{E_i}{E_{max}}$  represents the normalized residual energy with respect to the node's initial capacity. The term  $S_i$  measures the spatial centrality of node  $i$  defined as the inverse of its average distance to other nodes within cluster  $K$ , as shown in (9).

$$S_i = -\frac{1}{|C_K|} \sum_{j \in C_K} d(i, j) \quad (9)$$

Here,  $C_K$  denotes the total number of nodes in the cluster, and  $d(i, j)$  represents the Euclidean distance between nodes  $i$  and node  $j$ . Finally,  $L_i$  models the communication load, defined as the number of nodes located within the radio communication range  $r_{comm}$ .

$$L_i = \sum_{j \in C_K, j \neq i} \mathbb{I}(d(i, j) \leq r_{comm}) \quad (10)$$

The indicator  $\mathbb{I}(\cdot)$  equals 1 if the proximity condition is satisfied, and 0 otherwise. Once all evaluations are completed, the system selects as CH the node with the highest score according to the following selection rule (11).

$$CH_K = \arg \min_{i \in C_K} CH_{score(i)} \quad (11)$$

This dynamic selection strategy ensures a balanced distribution of workload, thereby preserving energy resources and significantly extending the operational lifetime of the network infrastructure.

#### 4.3. Data aggregation and transmission

This section presents an optimized methodology for data aggregation and transmission in clustered WSNs. The objective is to enhance energy efficiency and extend network lifetime by adopting a multi-hop communication strategy. In this scheme, CHs act as relay nodes to forward data to the BS, considering key parameters such as residual energy, neighborhood density, traffic load, and link reliability.

The connectivity between two CHs  $i$  and  $j$  is evaluated using the link quality factor  $LQF_{ij}$ , defined in (12).

$$LQF_{ij} = \frac{1}{1 + P_{loss,ij}} \times \frac{SNR_{ij}}{SNR_{th}} \quad (12)$$

In this expression,  $P_{loss,ij}$  denotes the packet loss probability between nodes,  $SNR_{ij}$  represents the effective signal-to-noise ratio, and  $SNR_{th}$  is the predefined reliability threshold for stable communication. A higher value of  $LQF_{ij}$  implies enhanced link quality.

To select the most suitable relay, a  $C_{ij}$  cost function is computed for each neighboring CH. This metric combines residual energy, the number of neighbors  $N_j$ , link quality, and the distance to the BS  $d(j, BS)$ .

$$C_{ij} = \frac{1}{E_j} + \frac{1}{N_j} + d(j, BS) - LQF_{ij} \quad (13)$$

To avoid consistently overloading the nodes with the lowest cost, our approach introduces a probabilistic relay selection mechanism. This method enables a more balanced distribution of traffic across the network.

$$P_{ij} = \frac{e^{-\mu C_{ij}}}{\sum_{k \in \mathbb{N}_i} e^{-\mu C_{ik}}} \quad (14)$$

Here,  $\mu$  is an adjustment coefficient used to balance deterministic selection and probabilistic behavior, while  $\mathbb{N}_i$  represents the set of adjacent CHs. Finally, the relay node for CH  $i$  is selected according to the following minimization rule.

$$Relay_i = \arg \min_{j \in \mathbb{N}_i} C_{ij} \quad (15)$$

Thanks to this configuration, data routing dynamically favors CHs with higher residual energy, stronger connectivity, and lower congestion, ensuring balanced load distribution and extending the overall network lifetime.

## 5. SIMULATION RESULTS AND DISCUSSION

This section presents and compares the simulations of the original DEEC, EEC and CAMP protocols with their improved versions by our proposed protocol based on KNN algorithm. Table 1 shows that both simulations used the same parameters.

Table 1. Simulation parameter

| Parameter                                                | Value                        |
|----------------------------------------------------------|------------------------------|
| Study area dimensions                                    | 100×100                      |
| Total number of sensor nodes (n)                         | 400                          |
| Number of rounds max                                     | 5000                         |
| CH election probability (p)                              | 0.1                          |
| BS coordinates                                           | 200×200                      |
| Electronic energy per bit $E_{elec}$                     | 50 nJ/bit                    |
| Amplification coefficient (free-space, $\epsilon_{fs}$ ) | 10 pJ/bit/m <sup>2</sup>     |
| Amplification coefficient (multipath, $\epsilon_{mp}$ )  | 0.0013 pJ/bit/m <sup>2</sup> |
| Reception energy per bit $E_{rx}$                        | 50 nJ/bit                    |
| Data packet size                                         | 500 bytes                    |
| Total simulation duration                                | 600 s                        |

The network topology analysis presented in Figure 1 clearly demonstrates the effectiveness of the proposed KNN-based clustering strategy in improving the overall organization of the WSN. Compared to the original protocols, the enhanced versions (DEEC-KNN, EEC-KNN, and CAMP-KNN) achieve a more optimized spatial distribution of CHs, significantly reducing their average distance to the BS. This improved placement eliminates inefficient or inactive CHs located at the network periphery, leading to more balanced cluster formation and improved coverage consistency across the deployment area.

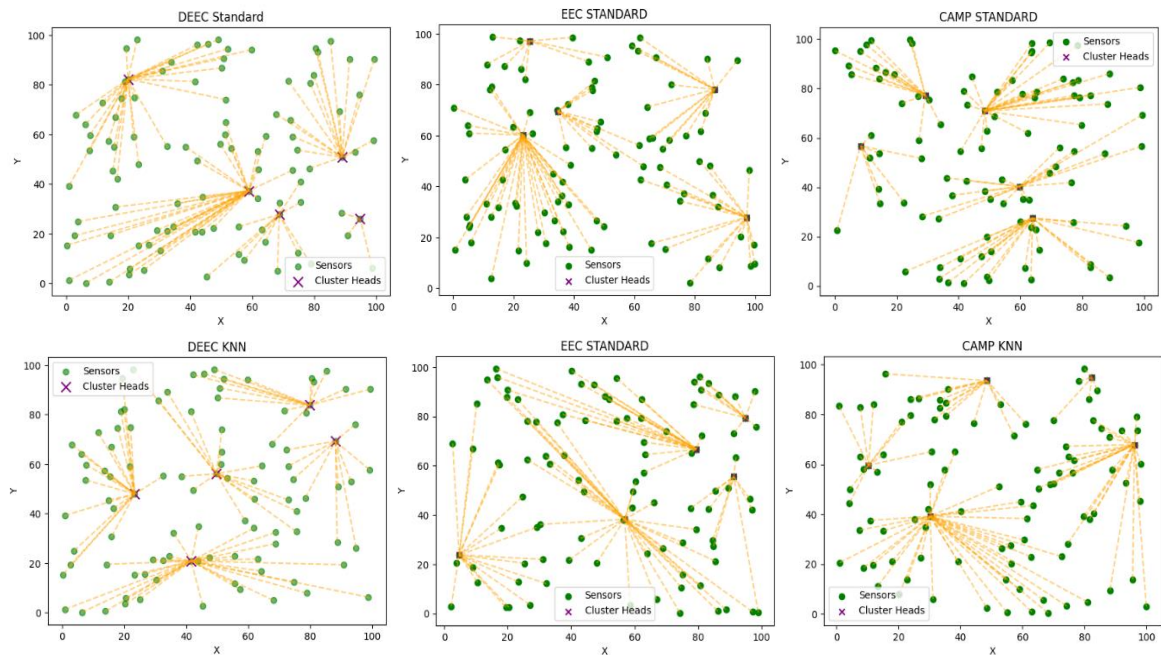


Figure 1. Performance results of the proposed DEEC-KNN, EEC-KNN, and CAMP-KNN implementations (X coordinate (m), Y coordinate (m))

In terms of energy efficiency (Figure 2), the results reveal a marked reduction in the average energy consumption per sensor node. This gain is mainly attributed to the optimized clustering process and the more selective CH election mechanism, which together minimize unnecessary long-distance transmissions and distribute communication tasks more evenly across the network. As a result, the overall energy load is better balanced, contributing to improved network sustainability.

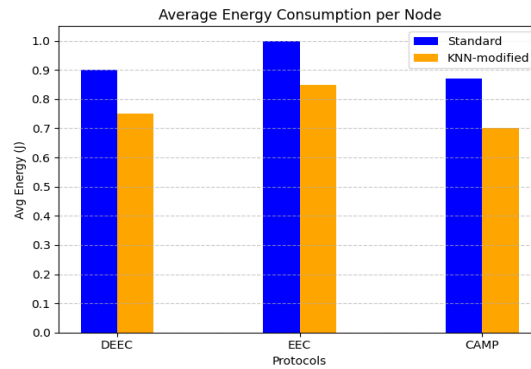


Figure 2. Comparison of average per-node energy consumption between original and KNN-modified protocols

The performance evaluation in terms of reliability and network lifetime (Figure 3) further highlights the advantages of the proposed method. The KNN-enhanced protocols consistently maintain a higher packet delivery ratio (Figure 3(a)), even under increasing network density, where traditional approaches typically experience performance degradation due to congestion and uneven energy depletion. Moreover, the monitoring of active nodes over time confirms a significant extension of the network lifetime (Figure 3(b)), indicating that the proposed strategy effectively mitigates premature node failures.

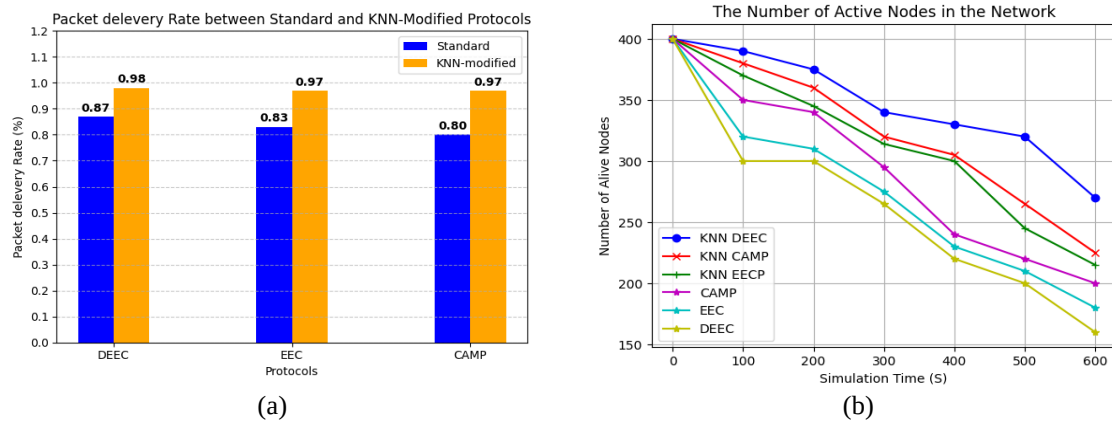


Figure 3. Evaluation of network performance; (a) packet delivery ratio and (b) number of active nodes

Finally, the scalability assessment (Figure 4) confirms the robustness of the proposed model when the network size increases from 100 to 800 nodes. Despite the growing complexity of the topology, the system maintains stable performance in terms of clustering quality, energy efficiency, and communication reliability. These results collectively validate the proposed KNN-based protocol as a scalable and energy-efficient solution for reliable data transmission and long-term operation in dense WSN environments.

The simulation results confirm the superiority of the KNN-optimized versions of DEEC, EEC, and CAMP compared to their conventional counterparts. These improvements are mainly reflected in better resource management, higher network robustness, and improved overall energy efficiency (Figure 4(a)). By optimizing cluster formation and refining CH selection, the proposed approach significantly reduces energy consumption while enhancing reliability. It also achieves a higher packet delivery ratio (Figure 4(b)), and

extends network lifetime (Figure 4(c)). These advantages remain consistent even in high-density network scenarios, demonstrating the effectiveness of the method for reliable and energy-efficient WSN routing.

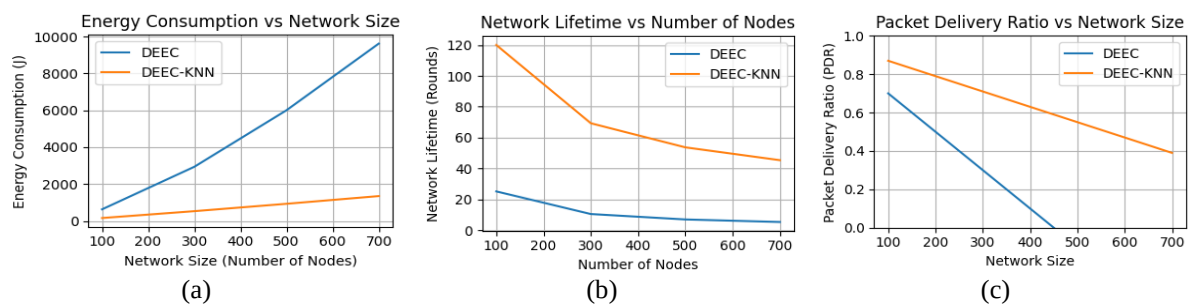


Figure 4. A scalability analysis; (a) analysis of energy consumption, (b) evaluation of network lifetime, and (c) packet delivery ratio performance

## 6. CONCLUSION

This study proposed an innovative approach to improve the performance of classic WSN protocols, including: DEEC, EEC, and CAMP, through the integration of the KNN algorithm. This method enables better identification of active nodes and more efficient management of cluster leaders, thus promoting optimal cluster organization. Cluster leader selection is based on residual energy and proximity to the BS, reducing energy consumption and communication delays. Simulation results show a significant increase in network lifetime and a decrease in the number of dead nodes compared to reference protocols. These improvements demonstrate the effectiveness of the proposed approach in enhancing the stability and performance of WSNs. Future work could extend this solution to dynamic environments and real-world deployments to evaluate its robustness under varying conditions.

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|--------------------|---|---|----|----|----|---|---|---|---|---|----|----|---|----|
| Adil Hilmani       | ✓ | ✓ |    | ✓  |    | ✓ |   | ✓ | ✓ | ✓ | ✓  |    | ✓ | ✓  |
| Yassine Sabri      |   |   | ✓  |    | ✓  |   | ✓ |   | ✓ | ✓ |    |    |   |    |
| Abderrahim Maizate | ✓ |   |    |    |    |   |   |   |   | ✓ |    | ✓  |   |    |
| Siham Aouad        |   | ✓ |    |    | ✓  | ✓ | ✓ |   | ✓ |   |    |    |   |    |
| Fouad Ayoub        | ✓ |   | ✓  |    |    |   |   | ✓ |   | ✓ |    |    |   |    |

C : **C**onceptualization

M : **M**ethodology

So : **S**oftware

Va : **V**alidation

Fo : **F**ormal analysis

I : **I**nterpretation

R : **R**esources

D : **D**ata Curation

O : Writing - **O**riginal Draft

E : Writing - Review & **E**dit

Vi : **V**isualization

Su : **S**upervision

P : **P**roject administration

Fu : **F**unding acquisition

## CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflict of interest related to the publication of this article.

## DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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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](mailto:adilhilmani@gmail.com).



**Yassine Sabri**    born on October 28<sup>th</sup>, 1984, in Rabat, Morocco, he received a B.Sc. in science, 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](mailto: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. His research interests lie in the areas of mobile networks and computing, wireless sensor networks, and embedded systems software for IoT. He is a member of IEEE. He can be contacted at email: [maizate@hotmail.com](mailto: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. She obtained her network engineering degree from the National School of Applied Sciences ENSA Tangier in 2005. Currently, she works, SDN, AI, virtualization, cloud computing, and security. She can be contacted at email: [siham.aouad@ensias.um5.ac.ma](mailto: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](mailto:ayoubfouadn@gmail.com).