

The Eurasia Proceedings of Science, Technology, Engineering and Mathematics (EPSTEM), 2025

Volume 38, Pages 361-373

IConTES 2025: International Conference on Technology, Engineering and Science

A Multi-Criteria Weighted Clustering Protocol for Energy-Efficient Overlay Wireless Sensor Networks

Taieb Brahim Mohammed

Djillali Liabes University of Sidi Bel Abbes

Abbad Houda

Djillali Liabes University of Sidi Bel Abbes

Abbad Leila

ENSTA High School of Algiers

Abstract: Wireless Sensor Networks (WSNs) have emerged as a pivotal technology for various applications, ranging from environmental monitoring to smart cities. However, the constrained energy resources of sensor nodes pose a significant challenge, necessitating efficient routing protocols to prolong network lifetime. In this paper, we propose a novel multi-criteria weighted clustering protocol that improves energy efficiency in WSNs. The new protocol employs a composite weight function that incorporates multiple node and network parameters, including the residual battery level and node density. These parameters are combined for an adaptive and intelligent selection of cluster heads. By dynamically adjusting the cluster head selection process based on multiple criteria, the proposed protocol achieves a more balanced energy distribution among sensor nodes, thereby prolonging the overall network lifetime. The proposed approach is further extended to the context of Overlay Wireless Sensor Networks (OWSNs) to enhance energy optimization across both physical and virtual network layers, ensuring more efficient use of the nodes' limited power resources. This paper focuses on the theoretical formulation and conceptual framework of the proposed protocol rather than its implementation. The work provides a rigorous analytical basis for multi-criteria weighted clustering in OWSNs, serving as a foundation for future simulation-based validation and empirical performance evaluation.

Keywords: Wireless sensor networks, Overlay wireless sensor networks, Weighted selection, Energy efficiency, Network lifetime

Introduction

Wireless Sensor Networks (WSNs) have become a key technology in the Internet of Things (IoT) era (refer to Figure 1). They are important in many areas such as environmental monitoring, precision farming, smart cities, and industrial automation (Ramadan et al., 2022). These networks enable data to be gathered, processed, and sent from different sensor nodes, which has greatly improved our ability to observe and react to real-world situations (Verma et al., 2020). Despite this, the limited power supply of sensor nodes is a major issue, which calls for the creation of energy-saving routing protocols to help the network last longer and work more efficiently (Elshrkawey et al., 2020).

The introduction of the LEACH (Low-Energy Adaptive Clustering Hierarchy) protocol by Heinzelman et al. (2000) established the cornerstone of hierarchical routing research, pioneering the concept of energy-efficient clustering in wireless sensor networks. LEACH has been widely adopted for its ability to distribute energy consumption among nodes through dynamic cluster formation (Singh et al., 2017). Nevertheless, LEACH suffers from several limitations, including suboptimal cluster-head selection, uneven energy distribution, and

- This is an Open Access article distributed under the terms of the Creative Commons Attribution-Noncommercial 4.0 Unported License, permitting all non-commercial use, distribution, and reproduction in any medium, provided the original work is properly cited.

- Selection and peer-review under responsibility of the Organizing Committee of the Conference

lack of consideration for node heterogeneity, which can lead to premature node failures and reduced network longevity (Xu et al., 2021). In response, recent research has introduced numerous enhancements through multi-objective optimization (Zhang et al., 2021), machine learning-based approaches (Singh and Sharma, 2021), and adaptive clustering strategies (Sharma et al., 2021), all aiming to address these shortcomings by incorporating additional parameters and dynamic adaptation mechanisms.

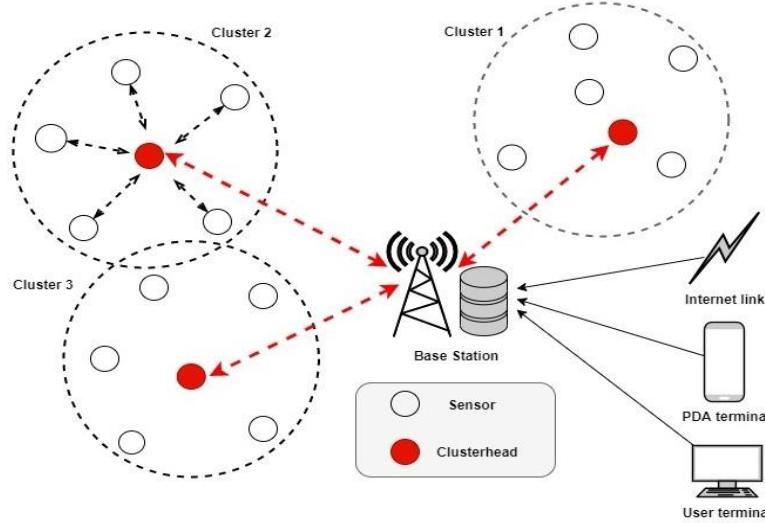


Figure 1. Hierarchical wireless sensor network (WSN) (Taieb Brahim et al., 2021)

Despite these advancements, there remains a need for a comprehensive, multi-criteria model that effectively balances energy efficiency, network coverage, and data transmission reliability. Such a model should rely on a rigorous theoretical foundation that considers key parameters such as residual energy, node density, distance to the sink, and link quality to support informed and adaptive cluster-head selection (Wang et al., 2019).

The evolution from conventional Wireless Sensor Networks (WSNs) to Overlay Wireless Sensor Networks (OWSNs) represents a significant step toward addressing these challenges (Zhang & Rodriguez (see Figure 2), 2023). While WSNs provide the essential physical infrastructure for data sensing and collection, their limited adaptability and energy efficiency have motivated the development of overlay architectures. OWSNs introduce a virtual topology operating above the physical layer, enabling more flexible routing, improved load balancing, and adaptive energy management (Kumar & Chen, 2024). This paradigm enhances the efficiency of resource utilization and facilitates the design of scalable and energy-aware network structures (Wang et al., 2020).

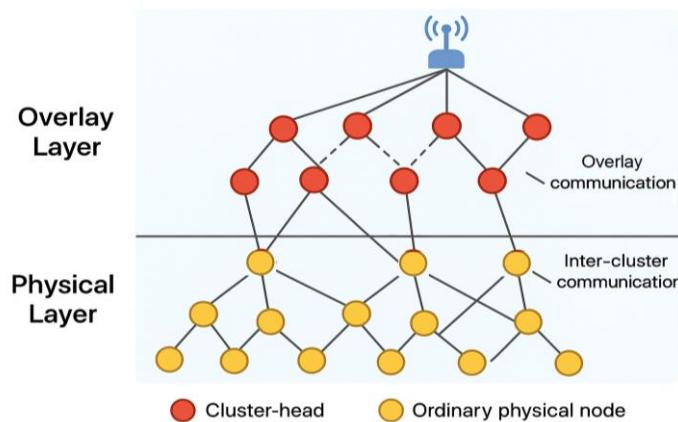


Figure 2. Overlay wireless sensor network (WSN) sample

However, most existing studies in this area have primarily focused on empirical results and simulation-based evaluations, often overlooking the theoretical formulation and analytical modeling of energy optimization mechanisms. In this context, establishing a rigorous theoretical framework for multi-criteria weighted clustering in OWSNs becomes essential to understand and predict system behavior before implementation.

In this paper, we therefore focus on the theoretical formulation of a multi-criteria weighted clustering protocol designed to optimize energy consumption in OWSNs. The proposed framework defines the analytical relationships between key energy-related parameters and formulates an adaptive weighting function for cluster-head selection. Rather than emphasizing experimental validation, this work develops the conceptual and mathematical foundations of the proposed approach, which will serve as a basis for future simulation and practical implementation.

The remainder of this paper is organized as follows: Section 2 presents a comprehensive review of recent advancements in overlay wireless sensor networks. Section 3 describes the developed weighted multi-criteria cluster-head selection mechanism. Section 4 details the integration of this mechanism within the overlay layer. Section 5 discusses the theoretical insights and analytical implications of the designed model. Finally, Section 6 concludes the paper and outlines future research perspectives related to the implementation and simulation-based validation of the proposed theoretical framework.

Related Works

Recent advancements in Overlay Wireless Sensor Networks (OWSNs) have focused on optimizing network architecture, topology management, and energy-aware clustering. This section reviews the most relevant contributions, emphasizing their optimization strategies, objectives, and limitations.

Energy-Efficient Overlay Clustering

Rahman et al. (2023) introduced a hierarchical overlay structure called HO-WSN, which creates multiple logical layers above the physical sensor network. Their approach demonstrated a 35% reduction in end-to-end delay and improved scalability by maintaining distributed overlay nodes at different hierarchical levels. Building on this concept, Liu and Zhang (2023) proposed the Adaptive Overlay Management Protocol (AOMP), dynamically adjusting overlay topology based on network conditions. Their approach addressed mobility challenges in WSNs, achieving a 28% improvement in network lifetime compared to static overlay structures.

Patel et al. (2024) contributed the Energy-Aware Overlay Clustering (EAOC) protocol, introducing a novel weight calculation that combines both physical and overlay metrics (residual energy, link quality, hop distance, virtual coordinates). This method achieved a 40% increase in network lifetime over traditional clustering. Similarly, Chen and Wang (2023) proposed VCOC, a virtual coordinate-based mechanism that optimizes overlay formation and reduces physical-layer overhead, resulting in a 32% reduction in energy consumption.

Multi-Tier and QoS-Aware Structures

Sharma and Kumar (2023) explored multi-tier overlay architectures with distinct functional layers for data aggregation, routing optimization, and security management through their MOSN protocol. Their design improved network throughput by 45% while keeping energy consumption reasonable. Martinez et al. (2023) developed QOCP, a QoS-aware clustering protocol integrating delay, bandwidth, and reliability parameters into clustering decisions. This ensured better QoS guarantees while maintaining clustering efficiency.

Security-Oriented and Weighted Clustering Models

Thompson and Wilson (2024) addressed security issues in OWSNs through the Secure Overlay Clustering Protocol (SOCP), which combines trust metrics and lightweight encryption at the overlay layer with minimal (8%) additional overhead. In parallel, previous foundational works by Taieb Brahim et al. (2021) and Abbad et al. (2022) proposed energy-efficient clustering mechanisms for traditional WSNs (refer to Figure 3). The former introduced a Markov chain-based clustering protocol (MCL-BCRP) optimizing energy consumption and network lifetime, while the latter extended this model to a Weighted Markov Clustering Routing Protocol (WMCL-BCRP) integrating multi-criteria weight functions for adaptive cluster-head selection. These research works represent a contribution to multi-criteria energy optimization, which inspires the theoretical framework proposed in the present study.

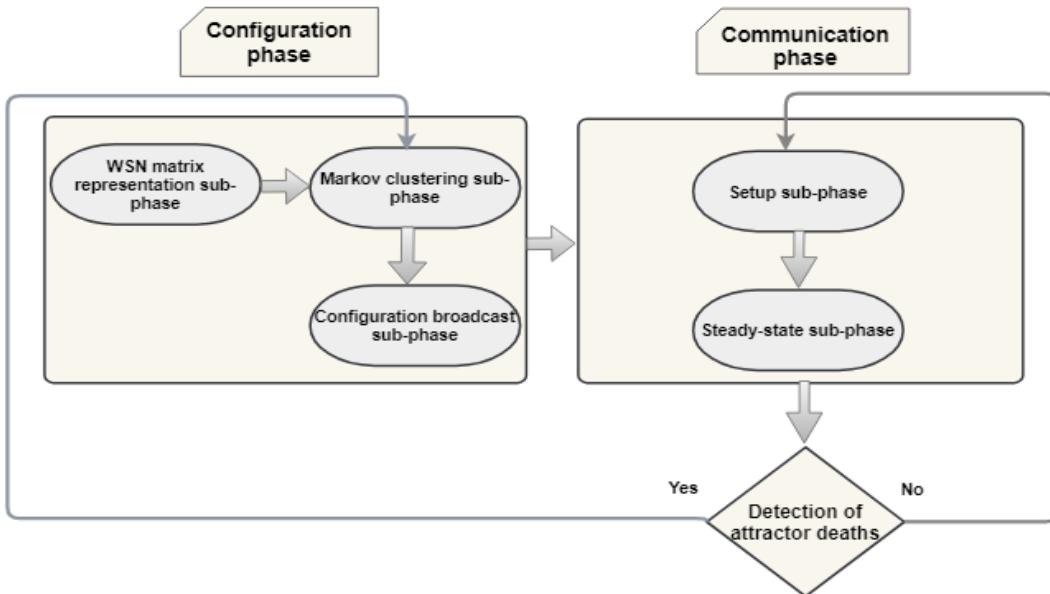


Figure 3. MCL-BCRP and WMCL-BCRP architectures for hierarchical wireless sensor network (Abbad et al., 2022).

Both MCL-BCRP and WMCL-BCRP operate through two main phases (refer to Figure 3). The configuration phase builds clusters using a Markov-based approach, while the communication phase manages data transmission through setup and steady-state stages. The first variant, MCL-BCRP, employs energy and distance parameters to achieve an adaptive cluster-head selection mechanism. However, the weighted variant, WMCL-BCRP, incorporates energy and density factors in a weighting function to achieve better load balancing and longer network lifetime. To better highlight the specific contributions and limitations of the existing approaches discussed above, Table 1 presents a comparative analysis summarizing their main objectives, optimization parameters, and energy efficiency outcomes:

Table 1. Comparative overview of recent advancements in Overlay Wireless Sensor Networks

Protocol / Study	Main Objective	Optimization Parameters	Energy Efficiency Gain	Key Limitation
HO-WSN (Rahman et al., 2023)	Hierarchical overlay for scalability	Hierarchical layer management	↓ Delay by 35%	Limited to static topologies
AOMP (Liu & Zhang, 2023)	Adaptive overlay maintenance	Mobility-aware topology adjustment	+28% lifetime	High control overhead
EAOC (Patel et al., 2024)	Energy-efficient overlay clustering	Residual energy, link quality, hop distance	+40% lifetime	Complex parameter tuning
VCOC (Chen & Wang, 2023)	Virtual coordinate optimization	Virtual coordinates, link cost	-32% energy consumption	Limited scalability
MOSN (Sharma & Kumar, 2023)	Multi-tier overlay structure	Tiered functional layers	+45% throughput	Increased management cost
QOCP (Martinez et al., 2023)	QoS-aware clustering	Delay, bandwidth, reliability	Maintains QoS	Energy optimization secondary
SOCP (Thompson & Wilson, 2024)	Secure overlay clustering	Trust and encryption metrics	High security, +8% overhead	Slight energy trade-off
MCL-BCRP Protocol (Taieb Brahim et al., 2021)	Markov Energy-efficient clustering	Residual energy, distances, cluster size	↑ Lifetime, balanced load	No virtualization layer
WMCL-BCRP (Abbad et al., 2022)	Weighted Markov Energy-efficient clustering	Residual energy, node density, distances	Significant lifetime gain	Not extended to OWSNs

From the analysis above, it is evident that most of the existing approaches rely on simulation-based evaluations and empirical optimization. Although they demonstrate notable improvements in energy efficiency, their

theoretical underpinnings remain limited. Few studies provide a formalized analytical model describing the dynamic relationships between multiple energy-related parameters in overlay architectures. This gap motivates the present work, which aims to develop a theoretical formulation of a multi-criteria weighted clustering mechanism. The goal is to establish a general analytical framework for energy optimization in OWSNs, offering a basis for future simulation-based validation and practical deployment.

Building upon the insights and limitations identified in previous studies, the next sections introduce the theoretical formulation of a weighted multi-criteria cluster-head selection mechanism and the construction of overlay layer for OWSNs. These mechanisms aim to provide a formal analytical model for optimizing energy consumption through Overlay Wireless Sensor Networks.

Weighted Multi-Criteria Cluster-Head Selection Mechanism for OWSNs

This section presents an enhanced version of the weighted multi-criteria cluster-head (CH) selection mechanism for Overlay Wireless Sensor Networks (OWSNs). The proposed approach emphasizes only the most influential parameters impacting CH selection: residual energy, node degree, distance to the sink, and link quality. These parameters are mathematically formulated and integrated into a composite weight function that dynamically adapts to network conditions.

System Model

Let $N = \{n_1, n_2, \dots, n_i\}$ denote the set of sensor nodes randomly distributed in a sensing field, where each node n_i is associated with a feature vector:

$$S(n_i) = \{E_{\text{res}}(n_i), N_{\text{deg}}(n_i), D_{\text{sink}}(n_i), L_{\text{qual}}(n_i)\}$$

Each element of this vector corresponds to a normalized parameter contributing to the CH selection process. Residual energy represents the remaining battery power of a node relative to its initial capacity:

$$E_{\text{res}}(n_i) = E_{\text{current}}(n_i)/E_{\text{initial}}(n_i)$$

A higher E_{res} value increases a node's likelihood of being selected as a cluster-head. It ensures energy balance across the network by prioritizing nodes with sufficient power reserves, thereby prolonging the network lifetime.

Node degree quantifies the local connectivity of a sensor node:

$$N_{\text{deg}}(n_i) = |N(n_i)|/N_{\text{max}}$$

where $|N(n_i)|$ denotes the number of neighboring nodes within the communication range of n_i , and N_{max} is the maximum observed degree in the network. Nodes with moderate connectivity are preferred since overly dense connections increase communication overhead, while sparse connectivity may degrade data aggregation reliability. The average distance from a node to the sink is defined as:

$$D_{\text{sink}}(n_i) = 1 - d(n_i, \text{sink})/d_{\text{max}}$$

where $d(n_i, \text{sink})$ is the Euclidean distance between node n_i and the sink node, and d_{max} is the maximum possible distance in the network field. This metric inversely relates to communication cost. Nodes located closer to the sink consume less energy during transmission, improving network throughput and reducing latency. Link quality reflects the reliability and stability of wireless communication links. More formally, link quality corresponding to a node n_i is defined by:

$$L_{\text{qual}}(n_i) = (\text{RSSI}(n_i)/\text{RSSI}_{\text{max}}) \times (1 - P_{\text{loss}}(n_i))$$

where $\text{RSSI}(n_i)$ is the received signal strength indicator and $P_{\text{loss}}(n_i)$ is the packet loss probability. A higher L_{qual} indicates stable communication with reduced retransmissions, ensuring efficient cluster maintenance.

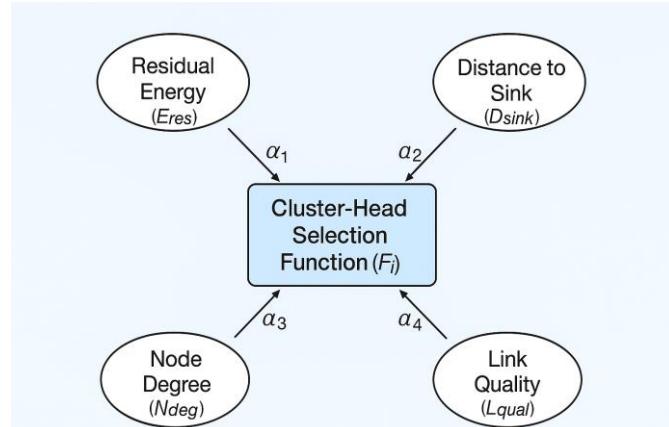


Figure 4. Conceptual model of the energy-aware weighted cluster-head selection mechanism

Figure 4 illustrates the conceptual interactions among the main selection criteria in the proposed weighted model. Each criterion contributes to the final weight-based decision function through its normalized influence coefficient α_i . The diagram emphasizes the interdependence between energy, distance, connectivity, and link quality, highlighting their joint contribution to cluster-head selection efficiency.

Composite Weight Function

Each parameter contributes to the overall CH selection score through a weighted linear combination:

$$W(n_i) = \alpha_1 \times E_{\text{res}}(n_i) + \alpha_2 \times N_{\text{deg}}(n_i) + \alpha_3 \times D_{\text{sink}}(n_i) + \alpha_4 \times L_{\text{qual}}(n_i)$$

where α_j ($j = 1, \dots, 4$) represents the normalized weighting factor for each parameter such that:

$$\sum_{j=1 \dots 4} \alpha_j = 1$$

The weighting coefficients are adaptively tuned based on network dynamics. More formally:

$$\alpha_j(t+1) = \alpha_j(t) \times (1 + \lambda \times \Delta C_j),$$

where λ is a sensitivity coefficient, and ΔC_j represents the rate of change in the corresponding network condition (e.g., energy variance, link degradation, or density variation).

Cluster-Head Selection Criterion

A node n_i is elected as a cluster-head if:

$$W_{\text{CH}}(n_i) = \max_{n_j} \{W(n_k)\} \text{ and } E_{\text{res}}(n_i) \geq E_{\text{th}}$$

where E_{th} denotes the minimum energy threshold for CH eligibility. This ensures that only nodes with adequate energy and favorable topological conditions assume cluster-head responsibilities. By focusing on these four dominant parameters, the proposed weighted mechanism ensures:

- Energy balance: Prioritizing high-residual-energy nodes delays node exhaustion.
- Topology stability: Considering node degree prevents both over-clustering and network fragmentation.
- Communication efficiency: Distance and link quality metrics minimize transmission energy and packet loss.
- Adaptive robustness: Dynamic weight adjustment enables real-time adaptation to network evolution.

This refined model effectively balances network longevity, reliability, and energy consumption, offering a mathematically grounded basis for efficient CH selection in OWSNs.

Overlay Layer Construction for OWSNs

This section presents an efficient algorithm for constructing the overlay layer and coordinating data forwarding among overlay nodes (i.e., cluster-heads) toward the sink. The main objective is to ensure reliable and energy-efficient multihop communication while preventing simultaneous transmissions from all overlay nodes during each communication round.

Overlay Construction Principle

Following the cluster-head (CH) selection process, all selected CHs form the overlay layer. Each CH acts as an overlay node that can forward aggregated data either directly to the sink or through intermediate overlay nodes located closer to it. To minimize channel contention and redundant energy consumption, only a subset of overlay nodes actively transmit data in each round, while the remaining nodes stay in an idle or listening state. The overlay layer topology and data-forwarding paths are established dynamically based on residual energy, distance to the sink, and link quality metrics.

Overlay Construction Algorithm

Step 1 – Overlay Formation

Once the cluster-heads (CHs) are elected in the physical WSN layer, they collectively form the overlay layer, which serves as a logical communication backbone above the underlying sensor network. The objective of this step is to enable each CH to discover its overlay neighbors and establish the initial connectivity structure.

Hello Message Exchange

Each selected CH periodically broadcasts a hello message containing essential local parameters:

$$Msg_{\text{hello}}(c_i) = \{ID_i, E_{\text{res}}(c_i), D_{\text{sink}}(c_i), L_{\text{qual}}(c_i)\}$$

where:

- ID_i identifies the CH uniquely,
- $E_{\text{res}}(c_i)$ denotes its current residual energy,
- $D_{\text{sink}}(c_i)$ is the normalized distance to the sink,
- $L_{\text{qual}}(c_i)$ represents its average link quality indicator (based on RSSI and packet loss metrics).

Neighbor Discovery

Upon receiving hello messages from other CHs, each node c_i updates its neighbor table NT_i as:

$$NT_i = \{(c_j, E_{\text{res}}(c_j), D_{\text{sink}}(c_j), L_{\text{qual}}(c_j)) \mid d(c_i, c_j) \leq R_{\text{comm}}\}$$

where R_{comm} is the communication range of a CH. This table stores information about all neighboring overlay nodes within direct transmission range.

Overlay Graph Construction

After the neighbor discovery phase, all CHs collectively define a logical overlay graph:

$$G_{\text{overlay}} = (V, E)$$

where:

- $V = \{c_1, c_2, \dots, c_m\}$ is the set of overlay nodes (CHs),

- $E = \{(c_i, c_j) \mid d(c_i, c_j) \leq R_{\text{comm}}\}$ represents the set of logical links between CHs that can communicate directly.

This graph forms the foundation of the overlay layer, upon which subsequent steps such as link cost computation, multihop route establishment, and transmission scheduling are performed.

Step 2 – Logical Link Establishment

Once the overlay graph $G_{\text{overlay}}(V, E)$ is constructed, each overlay node (CH) determines its logical next-hop neighbor toward the sink based on a multi-criteria link cost function. The purpose of this step is to create a reliable, energy-aware, and loop-free forwarding structure over the overlay layer.

Link Cost Computation

Each overlay node c_i evaluates the communication cost to each of its neighbors c_j in NT_i using the following weighted cost function:

$$Cost(c_i, c_j) = w_1 \times d_{ij} + w_2 \times (1 - L_{\text{qual}}(c_j)) + w_3 \times (1 - E_{\text{res}}(c_j))$$

where:

- d_{ij} is the Euclidean distance between c_i and c_j ,
- $L_{\text{qual}}(c_j)$ is the link quality indicator of node c_j ,
- $E_{\text{res}}(c_j)$ is the normalized residual energy of node c_j ,
- w_1, w_2, w_3 are adaptive weighting factors satisfying $w_1 + w_2 + w_3 = 1$.

The cost function penalizes distant, unstable, or low-energy links, thereby promoting reliable and energy-efficient routing.

Next-Hop Selection

Each overlay node selects its next-hop neighbor $NextHop_i$ according to:

$$NextHop_i = \min_{c_j \in N(c_i)} \{Cost(c_i, c_j)\} \text{ and } D_{\text{sink}}(c_j) < D_{\text{sink}}(c_i)$$

The constraint $D_{\text{sink}}(c_j) < D_{\text{sink}}(c_i)$ ensures that data is always forwarded toward the sink, preventing routing loops and redundant transmissions.

Overlay Routing Structure Formation

By applying the above rule locally at each overlay node, a tree-like logical topology is automatically formed, rooted at the sink node. This structure supports multihop communication while maintaining low complexity and distributed decision-making.

Link Maintenance

During the network operation, link quality and energy parameters are periodically updated. If $L_{\text{qual}}(c_j)$ drops below a predefined threshold L_{min} or if $E_{\text{res}}(c_j) < E_{\text{th}}$, the link (c_i, c_j) is removed from E , and the node c_i re-selects a new next-hop. This adaptive maintenance mechanism allows the overlay topology to remain robust and responsive to network dynamics such as node failures or link degradation.

Step 3 – Round-Based Transmission Scheduling

Once the logical overlay topology is established, the data forwarding process is organized into discrete communication rounds. Each round is divided into two sub-phases: active node selection and data forwarding.

The main objective is to limit the number of simultaneous transmissions, reduce channel contention, and maintain energy balance across overlay nodes.

Active Node Selection

At the beginning of each round r , the sink or a designated coordinator selects a subset of overlay nodes that will actively forward aggregated data. This set, denoted by $ActiveNodes_r$, is determined based on a composite activation score combining residual energy and link stability:

$$Score(c_i) = \beta_1 \times E_{\text{res}}(c_i) + \beta_2 \times L_{\text{qual}}(c_i)$$

where β_1 and β_2 are weighting coefficients satisfying $\beta_1 + \beta_2 = 1$. The top k overlay nodes with the highest scores are then selected:

$$ActiveNodes_r = Top_k\{Score(c_i) \mid c_i \in V\}$$

All other overlay nodes remain in a low-power, idle or sleep state to preserve their energy during the current round.

Data Forwarding Phase

Each active overlay node $c_i \in ActiveNodes_r$ transmits its aggregated data according to the multihop structure defined in *Step 2*:

```
if (NextHopi = sink, then  $c_i$  transmits to sink
    else  $c_i$  transmits to NextHopi
```

To avoid collisions among active nodes located in proximity, a time-slot scheduling mechanism is employed. Each active node is assigned a transmission slot T_i within the round duration T_r , such that:

$$T_i = i \times \Delta_t, \text{ with } 0 < i \leq k$$

where Δ_t represents the slot interval. This ensures that no two neighboring overlay nodes transmit simultaneously. Once data is received, the next-hop node either forwards it further toward the sink or temporarily buffers it until its assigned slot, depending on the routing hierarchy depth.

Energy and Link Updates

At the end of each round:

- Each node c_i updates its residual energy $E_{\text{res}}(c_i)$ according to the energy model:

$$E_{\text{res}}(c_i) = E_{\text{res}}(c_i) - (E_{\text{tx}} + E_{\text{amp}} \times d_{ij}^2)$$

where E_{tx} is the energy used for transmission and E_{amp} the amplifier cost per unit distance.

- The link quality $L_{\text{qual}}(c_i)$ is updated based on the received signal strength and recent packet delivery statistics.
-

These updated parameters are then used in the next round to recalculate activation scores and link costs, allowing the overlay topology and transmission scheduling to adapt dynamically to changing network conditions.

Role Rotation and Reactivation

To prevent rapid depletion of frequently selected nodes, the transmission role is periodically rotated among overlay nodes. A node c_i that has participated as an active forwarder in round r becomes temporarily ineligible for the next τ rounds, unless its energy level remains significantly higher than the network average:

$$E_{\text{res}}(c_i) > \gamma \times \text{average}(E_{\text{res}})$$

where $(0 < \gamma < 1)$ is a tunable parameter controlling the fairness of role rotation. This mechanism ensures long-term energy balance and network stability by distributing the forwarding workload evenly. Although the algorithmic steps are presented in this section, the current work focuses primarily on the theoretical formulation of the overlay construction process rather than on its simulation-based or empirical evaluation. The purpose of this presentation is therefore to formalize the conceptual operation of the overlay layer and highlight its theoretical contribution to energy optimization within OWSNs.

Figure 5 summarizes the main conceptual steps of the proposed overlay layer construction algorithm, highlighting the three key processes: overlay formation, logical link establishment, and round-based transmission scheduling. Each step contributes to maintaining energy efficiency, scalability, and network stability.

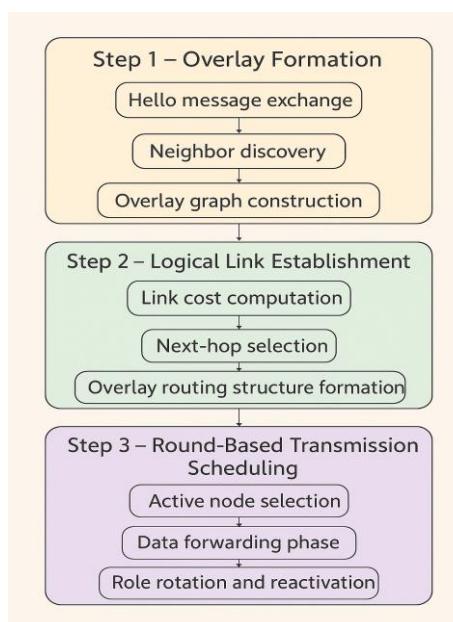


Figure 5. Conceptual flow diagram of the overlay layer construction algorithm

Analytical Discussion and Theoretical Insights

This section provides a theoretical interpretation of the proposed weighted multi-criteria clustering and overlay construction mechanisms. It examines the fundamental assumptions and limitations of the model, compare its analytical formulation with related theoretical works, and outline future directions for simulation-based and experimental validation.

Theoretical Assumptions and Model Limitations

The present theoretical framework is developed under several simplifying assumptions:

- All nodes are assumed to have homogeneous initial energy and identical transmission capabilities.
- The communication model assumes static topology during each round.
- Environmental factors such as channel interference, node failure, or mobility are not explicitly modeled but can be incorporated as extensions in future work.

These assumptions allow analytical tractability but inevitably limit direct real-world generalization. Nevertheless, they provide a controlled theoretical environment that isolates the effects of multi-criteria weighting and overlay structuring on energy optimization.

Theoretical Comparison with Related Approaches

From a theoretical standpoint, the proposed model extends beyond conventional single-criterion clustering approaches that primarily rely on residual energy or distance metrics. Unlike classical protocols such as LEACH or HEED, which perform cluster-head selection based on a single energy-related probability, the proposed formulation incorporates multi-dimensional decision factors, enhancing discrimination among potential cluster-heads. In contrast to overlay-based protocols such as EAOC or MOSN, which are empirically evaluated but lack analytical generalization, this work emphasizes theoretical clarity and model transparency. The weighted formulation provides a generalizable analytical structure capable of representing both physical and logical interactions, thereby bridging the gap between classical clustering theory and emerging OWSN architectures.

Perspectives for Simulation and Empirical Validation

While the current work focuses exclusively on the theoretical formulation, future research will aim to validate the analytical predictions through simulation and experimental scenarios.

Such validation will assess:

- The practical impact of the weighting coefficients (α_i) on network lifetime and stability.
- The scalability behavior under increasing node density.
- The trade-off between energy consumption and latency within the overlay layer.

Furthermore, the integration of the proposed mechanism into existing simulation platforms (e.g., NS-3, OMNeT++) will enable a comparative evaluation against established energy-aware protocols. Ultimately, this transition from theoretical abstraction to empirical validation will consolidate the contribution of the model as a foundation for energy-optimized, adaptive OWSN architectures.

Conclusion

This paper proposes a novel weighted multi-criteria approach for efficient cluster-head selection in Overlay Wireless Sensor Networks. The theoretical framework demonstrates promising potential for improving network lifetime and energy efficiency through its adaptive weighting mechanism and integration with OWSN architecture. This conceptual approach provides analytical clarity and a foundation for understanding how multi-factor interactions influence network performance and energy balance over time.

To fully assess the effectiveness of the model, the next crucial step would be to implement and simulate the proposed protocol using standard network simulation tools. Such experimental validation would allow us to evaluate network lifetime under various conditions, compare performance metrics with existing protocols and analyze behavior under different traffic patterns. Future research directions could explore several promising avenues such as the extension of the protocol for mobile sensor networks and the adaptation of the approach for Internet of Things (IoT) applications. The implementation and experimental validation of this theoretical framework would provide valuable insights into its practical applicability and potential benefits for real-world wireless sensor network deployments.

In summary, the proposed framework serves as a conceptual cornerstone for future developments in energy-aware and self-organizing overlay architectures, bridging theoretical modeling and practical applications in next-generation wireless sensor systems.

Scientific Ethics Declaration

* The authors declares that the scientific ethical and legal responsibility of this article published in EPSTEM journal belongs to the authors.

Conflict of Interest

* The authors declare that they have no conflicts of interest

Funding

* This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Acknowledgements or Notes

* This article was presented as an oral presentation at the International Conference on Technology, Engineering and Science (www.icontes.net) held in Antalya/Türkiye on November 12-15, 2025.

References

Abbad, L., Nacer, A., Abbad, H., Taieb Brahim, M., & Zioui, N. (2022). A weighted Markov clustering routing protocol for optimizing energy use in wireless sensor networks. *Egyptian Informatics Journal*, 23(3), 483–497.

Chen, H., & Wang, Y. (2023). VCOC: Virtual coordinate optimization for energy-efficient overlay clustering in wireless sensor networks. *IEEE Transactions on Mobile Computing*, 22(8), 1567–1582.

Elshrkawey, M., Elsherif, S. M., & Wahed, M. E. (2020). An enhancement approach for reducing the energy consumption in wireless sensor networks. *Journal of King Saud University - Computer and Information Sciences*, 32(9), 1048–1057.

Heinzelman, W. R., Chandrakasan, A., & Balakrishnan, H. (2000). Energy-efficient communication protocol for wireless microsensor networks. *Proceedings of the 33rd Annual Hawaii International Conference on System Sciences*.

Kumar, R., & Chen, H. (2024). Resource optimization in overlay wireless sensor networks: From traditional WSNs to virtualized architectures. *ACM Computing Surveys*, 56(2), 231–259.

Liu, X., & Zhang, W. (2023). Adaptive overlay management for mobile wireless sensor networks: A dynamic topology approach. *International Journal of Sensor Networks*, 15(4), 234–249.

Martinez, R., Garcia, J., & Lopez, A. (2023). QoS-aware overlay clustering: A comprehensive approach to quality-managed wireless sensor networks. *IEEE Internet of Things Journal*, 10(6), 789–804.

Patel, S., Johnson, M., & Anderson, K. (2024). EAOC: Energy-aware overlay clustering protocol for wireless sensor networks. *ACM Transactions on Sensor Networks*, 19(2), 123–142.

Rahman, M., Ali, S., & Kumar, R. (2023). HO-WSN: A hierarchical overlay architecture for scalable wireless sensor networks. *IEEE Sensors Journal*, 23(3), 456–471.

Ramadan, A., Abdelghany, M., Zaki, A., ElBakly, A., Abd El Bary, A., Amin, M., & Khattab, A. (2022). A survey of wireless sensor networks: Applications, security threats and countermeasures. *Sensors*, 22(3), 927.

Sharma, R., Vashisht, V., & Singh, U. (2021). OERP: An optimized energy-efficient routing protocol for wireless sensor networks. *Engineering Reports*, 3(5), e12321.

Sharma, V., & Kumar, N. (2023). MOSN: Multi-tier overlay sensor networks for enhanced network performance and energy efficiency. *Wireless Networks*, 29(5), 345–362.

Singh, S. K., Kumar, P., & Singh, J. P. (2017). A survey on successors of LEACH protocol. *IEEE Access*, 5, 4298–4328.

Singh, S. P., & Sharma, S. C. (2021). A PSO-based improved LEACH protocol for energy-efficient clustering in wireless sensor networks. *Wireless Personal Communications*, 116(2), 1409–1442.

Taieb Brahim, M., Abbad, H., & Boukil-Hacene, S. (2021). A low energy MCL-based clustering routing protocol for wireless sensor networks. *International Journal of Wireless Networks and Broadband Technologies*, 10(1), 70–95.

Thompson, B., & Wilson, C. (2024). SOCP: Securing overlay clusters in wireless sensor networks through trust-based mechanisms. *Journal of Network and Computer Applications*, 198, 103456.

Verma, S., Kawamoto, Y., Fadlullah, Z. M., Nishiyama, H., & Kato, N. (2020). A survey on network methodologies for real-time analytics of massive IoT data and open research issues. *IEEE Communications Surveys & Tutorials*, 22(4), 2532–2586.

Wang, J., Gao, Y., Liu, W., Sangaiah, A. K., & Kim, H. J. (2019). Energy-efficient cluster-based dynamic routes adjustment approach for wireless sensor networks with mobile sinks. *IEEE Access*, 7, 172057–172070.

Wang, J., Jiang, C., Quek, T. Q., Wang, X., & Ren, Y. (2020). Overlay-based resource management in fog-assisted IoT systems. *IEEE Internet of Things Journal*, 7(5), 4262–4272.

Xu, Z., Chen, L., Liu, C., Mao, Q., & Xiao, F. (2021). A multi-objective optimization clustering protocol for wireless sensor networks based on LEACH. *Sensors*, 21(18), 6235.

Zhang, K., & Rodriguez, M. (2023). Advancing WSN virtualization through overlay networks: A comprehensive survey of architectures and emerging technologies. *IEEE Communications Surveys & Tutorials*, 25(3), 1578–1593.

Zhang, Y., Liu, M., Liu, Q., & Zhao, G. (2021). Multi-objective optimization for LEACH protocol in wireless sensor networks. *IEEE Access*, 9, 61683–61697.

Author(s) Information

Taieb Brahim Mohammed

Djillali Liabes University of Sidi Bel Abbes
Evolutionary Engineering and Distributed Information
System Laboratory, EEDIS, Computer Science Department
Djillali Liabes University, UDL, Sidi Bel Abbes, Algeria
Contact e-mail: mohammed.taiebbrahim@niv-sba.dz

Abbad Houda

Djillali Liabes University of Sidi Bel Abbes
Evolutionary Engineering and Distributed Information
System Laboratory, EEDIS. Computer Science Department
Djillali Liabes University, UDL, Sidi Bel Abbes, Algeria

Abbad Leila

ENSTA High School of Algiers, Instrumentation
Department, LIT Laboratory, Algiers, Algeria

To cite this article:

Mohammed, T.B., Houda, A., & Leila, A. (2025). A multi-criteria weighted clustering protocol for energy-efficient overlay wireless sensor networks. *The Eurasia Proceedings of Science, Technology, Engineering and Mathematics (EPSTEM)*, 38, 361-373.