

# Consensus Optimization for Energy Efficiency in Heterogeneous Wireless Sensor Networks: Models, Techniques, and Future Directions

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## ABSTRACT

Energy efficiency continues to be a major concern in heterogeneous wireless sensor networks (HWSNs) due to unequal resource allocation and varying network dynamics. Consensus optimization offers an effective paradigm for enabling distributed management and achieving balanced energy utilization among heterogeneous sensor nodes. This review presents an in-depth examination of consensus-based models and techniques aimed at improving energy efficiency in HWSNs. It categorizes existing methodologies based on their operational mechanisms and analyzes how node heterogeneity impacts consensus formulation and overall network performance. In addition, it highlights key research limitations, including the lack of standardized classifications, inconsistent energy modeling, insufficient benchmarking, and limited analysis of the tradeoff between convergence and energy overhead. By synthesizing advances in adaptive weighting, clustering mechanisms, and hierarchical consensus architectures, the study proposes future research pathways for scalable, robust, and energy-efficient consensus systems. Ultimately, this review provides a foundation for developing sustainable optimization frameworks for next-generation sensor networks.

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## 1. INTRODUCTION

Wireless Sensor Networks (WSNs) has become a key technology that support applications in various fields, including environmental monitoring, healthcare, industrial automation, and smart cities [1][2]. A Wireless Sensor Network generally consists of numerous sensor nodes working together to sense, process and transmit packets to a Base Station (BS) or sink. These nodes often vary in terms of their computational capabilities, energy availability, and communication ranges, resulting to Heterogeneous Wireless Sensor Networks (HWSNs). The heterogeneity enhances scalability and robustness by providing hierarchical structures, and role-based assignment to the network, it also creates notable challenges in ensuring balanced energy consumption among nodes with varying capabilities [3][4]. Energy efficiency in HWSNs is not only a measure of reduced power consumption at individual nodes, but a fundamental determinant of overall network lifetime, fairness, and operational stability. Since sensor nodes are usually powered by batteries and often situated in remote or hard-to-reach locations, reinstating energy is often not feasible. Disparities in energy usage among diverse nodes can result in early node failure, network fragmentation, and reduce overall lifespan. Consequently, developing strategies that promote energy-efficient application while maintaining packet

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transmission quality is one of the most significant challenges in HWSNs research. Despite significant progress in clustering protocols, routing techniques, and adaptive transmission techniques, a common limitation remains: Current methods often focus on optimizing performance metrics in isolation and fail to ensure fairness and balanced energy usage throughout the network [5][6]. Additionally, many reviews in this area have primarily emphasized protocol-level optimizations or general energy-aware mechanisms, neglecting the potential of consensus optimization as a unifying framework. Consensus optimization, which is commonly employed in distributed systems and multi-tier networks, offers a structured approach to achieving agreement among nodes on global objective, such as energy-efficient cluster head selection, equitable load distribution, and adaptive data transmission techniques [7][8]. Its application in HWSNs has not been thoroughly explored, highlighting a gap in both theoretical frameworks and practical implementations [9][10]. This review aims to fill the gap by exploring how consensus-based models and techniques can enhance energy efficiency in heterogeneous wireless sensor networks. The study utilizes a model-driven approach, connecting equation-based formulations of energy consumption with consensus optimization techniques for clustering, routing, and transmission. This approach is selected for its ability to offer analytical clarity through explicit mathematical models, while also providing practical flexibility, as consensus rules can be tailored to heterogeneous and multi-tier architectures. This review aims to contribute in three key areas. First, it synthesizes the scattered body of work on consensus optimization and energy-efficient HWSNs into a coherent framework. Second, it provides a critical assessment of the strengths and weaknesses of the existing consensus-based techniques regarding energy efficiency, scalability, and network longevity. Third, it identifies open challenges and processed future directions, such as consensus under adaptive topologies, integration with energy harvesting, and synergy with machine learning for predictive optimization.

Overall, this review is valuable for both researchers and practitioners aiming to design energy-efficient heterogeneous wireless sensor networks. By framing consensus optimization as a unifying perspective, it extends the conversation beyond protocol-focused methods and emphasizes new avenues for developing resilient, equitable, and sustainable next-generation sensor networks. The key contributions are as follows:

- A detailed categorization and evaluation of consensus-driven models according to their functional principles, hierarchical architecture, and management strategies within heterogeneous wireless sensor networks.
- The formulation of an integrated framework that promotes energy-efficient management by illustrating how distributed decision processes and adaptive weighting techniques collectively reduce energy usage while ensuring stable and reliable communication among diverse sensor nodes.
- A critical identification of existing limitations and emerging research pathways aimed at fostering the evolution of next-generation intelligent and energy-optimized HWSNs.

The subsequent section in this manuscript is organized as follows: Section 2 presents a review of similar works alongside a Table of summary of the reviewed literature. Section 3 provides fundamentals of heterogeneous wireless sensor networks, including its characteristics of HWSNs, challenges in energy management, and comparison with homogenous WSNs. Section 4 provides consensus optimization: conceptions and relevance, including definitions and principles of consensus optimization, role in distributed decision-making and energy balancing, benefits for multitier and multi-hop communication. Section 5 discusses Consensus optimization techniques for energy efficiency in HWSNs, including its clustering-based consensus transmission strategies in consensus load balancing and weighting mechanisms, consensus in multi-tier architectures, and case studies of algorithm adopted with consensus. Section 6 presents an open research challenges, including its scalability to ultra-dense IoT networks, consensus under dynamic topologies and mobility, security and fault-tolerant consensus in HWSNs, integration with AI/ ML for predictive optimization, and consensus under energy harvesting and renewable-powered WSNs. Finally, Section 7 concludes the review article. Energy imbalance in HWSNs emerges systematically from unequal role assignments and traffic load, such that nodes with higher connectivity or cluster-head responsibilities dissipate energy much faster than peripheral nodes. This results in spatially non-uniform energy depletion, widely known as the energy hole problem, which gradually undermines overall network performance.

## 2. REVIEW OF SIMILAR WORKS

In [12], the authors introduced an Energy-based Multi-objective Donkey Smuggler Optimization Algorithm (EM-DSOA) to address critical challenges in wireless sensor network applications, including energy limitation, latency, scalability, and security. The framework integrates dynamic clustering, adaptive routing, and block-chain-based secure data transmission within a multi-objective optimization setting. Simulation results demonstrate remarkable performance gains, achieving a 99.1% energy efficiency improvement, a 91% reduction in packet loss, and nearly a 1000% throughput enhancement, while maintaining low latency suitable for real-time applications. Despite these strong results, the framework lacks holistic consensus mechanisms,

coordinated load balancing, and hierarchical management, resulting in fragmented optimization that limits scalability and real-world applicability in heterogeneous WSNs.

Similarly, the work in [13] proposed the Hierarchical Chimp Optimization Algorithm (HChOA), which unifies clustering and multi-hop routing into a single optimization framework to overcome energy and bandwidth constraints, particularly in underwater sensor networks. By jointly addressing the overburdening of cluster heads and relay nodes near the base station, HChOA reduces the complexity associated with dual-algorithm designs. Simulation comparisons against LEACH, TEEN, MPOS, POS, and IPSO-GWO show consistent improvements in energy efficiency and network lifetime. However, like [12], this approach does not incorporate consensus weighting, coordinated load balancing across hierarchy levels, or system-wide integration, which constrains unified optimization and scalability in heterogeneous deployments.

While both studies demonstrate that meta-heuristic-driven unified clustering and routing can significantly enhance energy efficiency, they remain algorithm-centric and scenario-specific, with limited consideration of consensus-based decision making, cross-layer coordination, and heterogeneous node capabilities. In contrast, the proposed review article, the propose review article systematically examines consensus optimization models, distributed coordination strategies, and hierarchy-aware energy management across diverse HWSN architectures. Rather than proposing a single algorithm, the review synthesizes existing techniques, identifies structural gaps, and outlines future directions toward scalable, unified, and real-world deployable consensus-driven HWSNs. Despite notable progress in recent studies, existing solutions still provide only partial remedies to the multifaceted challenges of Heterogeneous Wireless Sensor Networks (HWSNs).

In [14], the authors advance prior block-chain-based security approaches by proposing an Energy-aware Proof-of-Authority (EA-PoA) consensus mechanism tailored to heterogeneous sensor environments. By dynamically rotating block proposers based on residual energy, the scheme improves network lifetime by approximately 10% while maintaining data integrity and confidentiality. Furthermore, the introduction of a multi-level block-chain architecture, comprising cluster-level block-chains interacting with a master block-chain, addresses scalability limitations observed in earlier monolithic PoA designs and significantly enhances block formation rates. These contributions effectively bridge gaps related to energy-aware consensus design and scalable secure data management in HWSNs. However, the solution remains incomplete, as it overlooks the tight integration with routing, load balancing, consensus weighting, and hierarchical network management mechanisms. As a result, the framework operates in a fragmented manner, limiting holistic optimization, adaptability to dynamic network conditions, and real-world energy efficiency at scale.

Similarly, the work in [15] improves upon earlier trust- and energy-aware routing schemes by introducing an Improved Sensor Localization with an Intelligent Trust Model for HWSNs (ISL-ITMH). By combining energy consumption modeling, trust-based energy monitoring, and optimized data transmission, the framework addresses key gaps in secure communication and energy-efficient operation for large-scale IoT-driven HWSNs. Extensive NS-3 simulations demonstrate superior performance across multiple metrics, including energy efficiency, packet delivery ratio, throughput, latency, and security score. While these results validate the effectiveness of localized trust and energy optimization, the approach still lacks a unified cross-layer design. The absence of coordinated routing and load-balancing strategies, hierarchical control mechanisms, and consensus-aware decision weighting prevents the framework from achieving system-wide scalability, resilience, and sustained energy efficiency in realistic heterogeneous deployments.

Overall, although these studies successfully address specific gaps in security, energy awareness, and localized optimization, they stop short of delivering a comprehensive, integrated solution. This persistent fragmentation underscores the need for holistic, cross-layer frameworks that jointly consider intelligence, routing, load balancing, consensus mechanisms, and hierarchical management to fully unlock the potential of self-evolving HWSNs.

In [16], the authors focus on the inherent challenges of energy efficiency, security, and routing reliability in heterogeneous wireless sensor networks (HWSNs), where nodes with diverse capabilities coexist under stringent resource constraints. Recognizing that premature energy depletion of low-capability sensors significantly shortens network lifetime, the study proposes an energy-aware and secure routing protocol, termed TDDSRP. The protocol evaluates sensor nodes based on residual energy and direct security values, integrating these parameters into a unified energy–security metric to guide routing decisions. Through MATLAB-based simulations, TDDSRP demonstrates improved performance over existing routing schemes in terms of energy efficiency, throughput, and security robustness, thereby addressing gaps in earlier approaches that treated energy optimization and security as independent design objectives. Nevertheless, the proposed solution remains localized and protocol-centric, as it does not consider holistic integration across routing, load-balancing strategies, consensus-aware decision mechanisms, or hierarchical network management. This lack of cross-layer coordination results in a fragmented framework that limits unified optimization, scalability, and sustained energy efficiency in large-scale, real-world HWSN deployments.

Building on these insights, the study in [17] investigates IoT-based Wireless Sensor Networks (IoT-WSNs) deployed in smart city environments, where high energy demand, limited network lifetime, and

escalating security threats pose significant barriers to long-term sustainability. To mitigate these challenges, the authors propose a block-chain-enabled framework that leverages distributed ledgers and smart contracts to reduce redundant data transmissions, lower communication overhead, and enhance security assurance. The incorporation of block-chain-based clustering facilitates energy-aware sensing, efficient resource allocation, and secure spectrum access, while cognitive radio technology is employed to optimize spectrum utilization. Simulation results indicate that the proposed framework outperforms existing techniques in terms of energy efficiency, spectrum sensing accuracy, and security performance, thereby advancing the state of the art in secure and energy-aware IoT-WSNs. However, despite these promising gains, the framework does not provide a comprehensive, system-level integration of routing optimization, load balancing, consensus weighting, and hierarchical control mechanisms. Consequently, the absence of coordinated cross-layer intelligence constrains scalability, adaptability to dynamic network conditions, and practical energy efficiency in heterogeneous smart city deployments.

Overall, while both studies make meaningful contributions toward energy-aware and secure operation in HWSNs and IoT-WSNs, their solutions remain partial and fragmented. The lack of unified cross-layer design and holistic network management underscores an unresolved research gap, motivating the need for integrated, self-adaptive frameworks capable of jointly addressing energy efficiency, security, routing, consensus mechanisms, and hierarchical scalability in next-generation HWSNs.

In [18], the authors propose a Double Deep Q-learning-based Dynamic Arithmetic Reinforcement Learning (DQARL) framework to enhance energy-efficient clustering and scheduling-driven routing in heterogeneous wireless sensor networks (HWSNs). The approach adopts a multi-phase optimization strategy. In the first phase, Hunter-Prey Optimization (HPO) is employed to identify optimal cluster heads based on multiple fitness criteria, enabling balanced energy utilization across heterogeneous nodes. The second phase introduces a distributed duty-cycling mechanism, in which sensor nodes operate in sleep, listen, and transmit modes to improve network lifetime through efficient energy scheduling. In the final phase, a Practical Byzantine Fault Tolerance (PBFT) algorithm is incorporated to support sustainable routing and reduce end-to-end transmission delay by selecting reliable communication paths between source nodes and cluster heads. Simulation results indicate that the proposed framework significantly reduces energy consumption and achieves fault tolerance exceeding 95% when compared with existing schemes. Despite these promising outcomes, the solution remains modular and loosely coupled, as it lacks comprehensive cross-layer integration of routing and load-balancing strategies, consensus weighting mechanisms, and hierarchical network management. This fragmentation limits unified optimization, scalability under dynamic conditions, and practical energy efficiency in large-scale HWSN deployments.

Similarly, the study in [19] introduces two reinforcement learning-based techniques-Linear Optimization State-Action-Reward-State--Action (LO-SARSA) and a Proportional Optimization Policy Gradient Method (PO-PGM)-to jointly address energy-aware cluster head selection and adaptive routing. Cluster head selection is formulated as a reinforcement learning problem, where LO-SARSA derives policies based on residual energy and inter-node distance, while PO-PGM leverages a neural network to enable dynamic and intelligent routing decisions. Simulation results demonstrate that the proposed methods outperform conventional approaches in terms of energy consumption, network lifetime, and data delivery ratio, achieving approximately a 20% improvement in network lifetime over benchmark schemes. Nevertheless, the framework focuses primarily on localized decision-making and does not incorporate holistic integration across routing, load balancing, consensus-aware coordination, and hierarchical control. As a result, the approach falls short of delivering a unified and scalable optimization framework suitable for real-world heterogeneous sensor networks.

In [20], the authors address the dual challenges of energy consumption and sensing accuracy by proposing a cascaded sensor dynamic activation and information fusion algorithm. The scheme adaptively activates the most suitable sensor nodes for a given sensing task through a joint event-driven and phase-ranking activation mechanism, achieving optimized sensing performance with reduced energy expenditure. To further enhance accuracy, data collected from activated nodes are fused using an enhanced distributed Kalman information fusion technique, which minimizes estimation variance and improves sensing reliability. Simulation results confirm that the proposed approach significantly reduces the number of dead nodes due to energy depletion and decreases average sensing error by nearly 62.1%, approaching near-zero estimation error under certain conditions. However, similar to other contemporary solutions, the framework does not consider integrated routing optimization, load balancing, consensus weighting, or hierarchical network organization, leading to a fragmented design that constrains system-wide scalability, adaptability, and long-term energy efficiency in heterogeneous deployments.

Overall, while these studies leverage advanced intelligence-driven and optimization-based techniques to address specific challenges in energy efficiency, fault tolerance, and sensing accuracy, they remain limited in scope due to the absence of unified, cross-layer integration. This persistent fragmentation highlights a critical research gap and reinforces the need for holistic, self-adaptive HWSN frameworks that jointly address

clustering, routing, load balancing, consensus mechanisms, and hierarchical management to achieve scalable and energy-efficient real-world deployments. Table 1 depicts the summary of reviewed literature.

Table 1. Summary of Reviewed Literatures

| Reference | Work Done                                                                                                                                       | Method Used                                                                    | Pros                                                                                                                                                                                                                                       | Cons                                                                                        |
|-----------|-------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------|
| [11]      | Introduction of heterogeneity-aware framework that incorporates residual energy, transmission range, and functional roles into node operations. | Improved Particle Swarm Optimization (IPO) algorithm.                          | Developed algorithm shows significant improvements over existing protocols: a 32.7% reduction in per-round energy utilization compare to LEACH, a 28% maximized network lifetime, and a 63% minimized the energy variance across the nodes | Lack of a unified framework technique, and fragmented energy models and evaluation metrics. |
| [12]      | The following were carrying out: energy efficiency, packet loss reduction, and throughput maximization.                                         | Energy-based Multi-Objective Donkey Smuggler Optimization Algorithm (EM-DSOA). | Developed algorithm show improvements over existing algorithms in terms of energy efficiency 99.1%, and throughput gains close to 1000%.                                                                                                   | Lack of a unified framework technique, and fragmented energy models and evaluation metrics  |
| [13]      | They work on energy efficiency and network lifetime                                                                                             | Hierarchical Chimp Optimization Algorithm (HChOA).                             | The developed protocol improves energy efficiency and network lifetime                                                                                                                                                                     | Lack of a unified framework technique, and fragmented energy models and evaluation metrics. |
| [14]      | They work on energy efficiency and throughput.                                                                                                  | Energy-aware Proof-of-Authority (EA-PoA).                                      | The developed protocol improves scalability and doubling block formation, also based on residual energy, extending network life time bt 10%.                                                                                               | Lack of a unified framework technique, and fragmented energy models and evaluation metrics. |
| [15]      | They work on energy efficiency, packet delivery ratio, routing overhead, security scores, throughput, and latency                               | Intelligent Trust Model for HWSNs (ISL-ITMH)                                   | The developed algorithm performs better than the existing algorithms in terms of aforementioned parameter metrics.                                                                                                                         | Lack of a unified framework technique, and fragmented energy models and evaluation metrics. |
| [16]      | They work on energy efficiency, throughput, and security performance.                                                                           | Time Division Data Delivery and Scheduling Routing Protocol (TDDS-RP).         | Simulation shows the developed protocol superiority over existing protocols in terms of energy efficiency, throughput, and security performance.                                                                                           | Lack of a unified framework technique, and fragmented energy models and evaluation metrics. |
| [17]      | Energy demand, maximized network life time, and security risk.                                                                                  | A block-chain enabled framework.                                               | Proposed technique outperforms existing techniques in terms of energy efficiency, spectrum accuracy, and security.                                                                                                                         | Lack of a unified framework technique, and fragmented energy models and evaluation metrics. |
| [18]      | They work on network lifetime, energy consumption.                                                                                              | Double deep Q-learning Dynamic Arithmetic Reinforcement Learning (DQARL).      | Proposed algorithm performs better than the existing algorithms in terms of energy consumption and tolerant of greater than 95% of fault.                                                                                                  | Lack of a unified framework technique, and fragmented energy models and evaluation metrics. |
| [19]      | Energy usage, network lifetime, and data delivery ratio                                                                                         | Proportional Optimization Policy Gradient Method (PO-PGM) .                    | Proposed algorithm outperforms the existing algorithms in terms of energy usage, network lifetime, and data delivery ratio by a 20% gain in network life time over existing schemes.                                                       | Lack of a unified framework technique, and fragmented energy models and evaluation metrics. |

| Reference | Work Done                                  | Method Used                                     | Pros                                                                                                                                                              | Cons                                                                                        |
|-----------|--------------------------------------------|-------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------|
| [20]      | Energy consumption and sensing performance | Enhanced distributed Kalman information fusion. | Proposed technique outperforms the existing techniques in terms of dead nodes, energy a decrease in average error sensing by almost zero and 62.1%, respectively. | Lack of a unified framework technique, and fragmented energy models and evaluation metrics. |

While, most researchers focused on energy efficiency and heterogeneous wireless sensor networks, they paid little attention to the followings: comprehensive integration of consensus and energy model thereby bridging clustering, routing and load-balancing technique, unified framework techniques that creates a hybrid energy role hierarchy consensus hence combines energy-aware gradient descent, consensus weighting, and hierarchy management to improve distributed optimization, and critical analysis of the existing approaches to highlights improvements in scalability, fairness, and energy balance. Table 1 is the summary of the reviewed literature carry out in this field.

### 3. FUNDAMENTALS OF HETEROGENEOUS WIRELESS SENSOR NETWORKS

Heterogeneous Wireless Sensor Networks are composed of sensor nodes with non-uniform energy, computation, memory, and communication capabilities, enabling differentiated functional roles such as sensing, aggregation, relaying, and coordination. This structural heterogeneity improves adaptability through role-based task allocation and hierarchical communication, and enhances efficiency by reducing redundant transmissions and optimizing energy consumption across resource-rich and resource-constrained nodes [21][22]. The following will be briefly discussed to ensure that this section is understood: characteristics of HWNs, challenges in energy management, and comparison with homogeneous WSNs.

#### 3.1. Characteristics of HWSNs

Heterogeneous Wireless Sensor Networks (HWSNs) differ from homogeneous networks by introducing nodes with varying capabilities in energy, processing, and transmission. This diversity improves flexibility and efficiency but also introduces complexity in managing network functions. Understanding their key characteristics is critical for addressing challenges in energy efficiency and performance optimization. The following will be briefly discussed to ensure that this subsection is understood: Node Heterogeneity, Energy Imbalance, and Multilevel Clustering [23][24].

##### Node Heterogeneity

In HWSNs, sensor nodes vary in their computational capabilities, residual energy, and transmission power. Resource-rich nodes are regularly deployed as CHs or data aggregators, while energy-limited nodes carry out sensing and short-range communication. This diversity enhances scalability and reliability, yet makes cluster formation and energy allocation more complex [25][26]. Node heterogeneity directly enables distributed decision-making by allowing more capable nodes (e.g., cluster heads or sink nodes) to perform complex tasks such as data fusion, routing optimization, and local learning. Conversely, less capable nodes focus on sensing and basic forwarding, thereby reducing network-wide overhead while improving scalability and responsiveness.

##### Energy Imbalance

Variations in energy reserves among sensor nodes frequently result in imbalanced workload distribution, where resource-rich sensor nodes deplete their resources faster due to frequent CH assignments or multi-hop transmissions. Energy imbalance minimizes overall network lifespan and need approaches such as load-aware clustering, duty cycling, or consensus optimization to prolong operation [27][28].

##### Multilevel Clustering

For more efficient utilization of energy and communication resources, heterogeneous wireless sensor networks commonly implement multilevel clustering. In this method, nodes are organized into hierarchical structures where low-tier nodes sense and send data to mid-tier nodes, which then forward aggregated data to high-tier nodes or directly to the BS. This approach minimizes communication overhead and balances energy utilization across the hierarchy [27].

### 3.2. Challenges in Energy Management

Managing energy efficiently is a key challenge in heterogeneous wireless sensor networks because sensor nodes possess limited and imbalanced energy resources. Variations in workload, transmission demands, and clustering assignments often increase the depletion of certain nodes, resulting to network instability. Addressing these challenges needs dynamic approaches that balance energy usage while sustaining reliable network operation. Protocols must therefore address: Table 2 shows the criteria for protocol challenges that need to be addressed [29][30].

Table 2: Criteria for protocol challenges to be addressed: [31][34]

| Criteria                    | Description                                                                                              |
|-----------------------------|----------------------------------------------------------------------------------------------------------|
| Fair role Assignment        | To prevent early energy depletion of resource-rich nodes                                                 |
| Adaptive routing techniques | That reduce redundant communications and balance networks                                                |
| Consensus-driven methods    | That allows distributed decision-making for energy assignment, clustering and scheduling.                |
| Scalability issues          | Since the incorporation of multiple sensor nodes types complicates network management as scale increases |

### 3.3. Comparison with Homogeneous WSNs

Consensus optimization is mainly well-suited to HWSNs because node heterogeneity intrinsically presents distributed decision-making across sensors with uneven energy, computation, and communication capabilities. Unlike homogeneous WSNs where uniform policies often suffice, HWSNs require continuous coordination among diverse nodes to achieve global objectives such as balanced energy consumption, adaptive clustering, and reliable data fusion. Consensus mechanisms enable these heterogeneous agents to iteratively align local states with global network goals without centralized control, making them more critical for scalability, resilience, and efficiency in heterogeneous environments than in homogeneous ones [35][36].

## 4. CONSENSUS OPTIMIZATION: CONCEPTIONS AND RELEVANCE

Efficient management among distributed sensor nodes is a principal challenge in HWSNs, where variations in energy, transmission range, and computation regularly lead to imbalanced workloads. Conventional centralized optimization techniques, though effective in small-scale scenarios, speedily become impractical due to high transmission overhead, single-point failures, and limited scalability. Consensus optimization has emerged as a promising solution, enabling sensor nodes to collectively derive network-wide decisions based on localized exchanges. By combining mathematical precision with distributed flexibility, consensus optimization ensures energy-aware management, balanced resource usage, and robust performance in multi-tier and multi-hop domains. The following will be briefly discussed to ensure that this section is understood: definition and principles of consensus optimization, role in distributed decision-making and energy balancing, and benefits for multi-tier and multi-hop communication [37][38]. The Figure 1 illustrates how consensus optimization allows distributed decision-making and energy balancing among interconnected heterogeneous sensor nodes in a wireless sensor network.

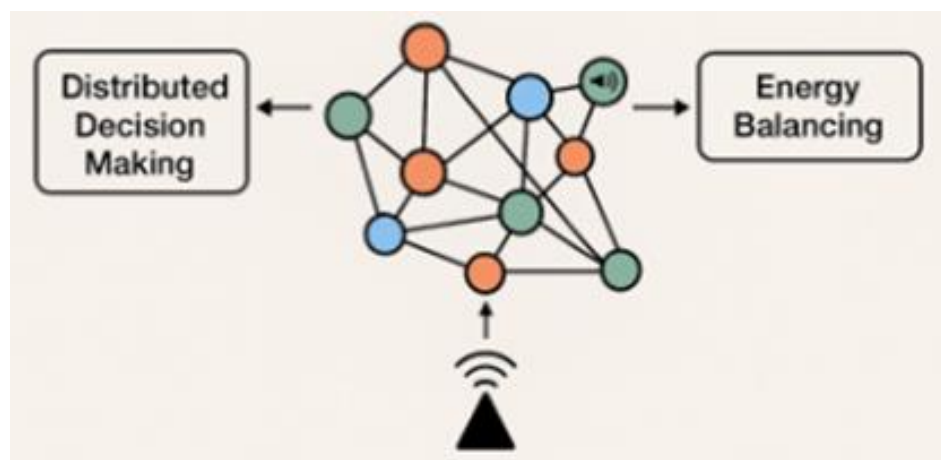


Figure 1: Consensus Optimization in HWSNs [39]

#### 4.1. Definition and Principles of Consensus Optimization

Consensus optimization is a distributed mathematical structure intended to attain agreement among multiple tiers or sensor nodes on a unified aim while respecting local limitations and information. In the context of WSNs, consensus optimization allows sensor nodes to mutually derive optimal configurations, such as choosing CH, routing paths, or communication schedules via iterative information exchange. The concept is based on distributed averaging; each node refines its state by integrating local data with neighboring nodes until a network-wide agreement is achieved. This decentralized nature eradicates reliance on a central controller, minimizing bottlenecks and improving scalability [40]-[42]. The update rule defines how node  $i$  iteratively adjust its state  $x_i^t$  by combining a local gradient descent on its objective function with an energy- and link-aware consensus term, weighted by neighbors and modulated through the coupling factor  $\Phi_{ij}$  as seen in equation (1)

Consensus Optimization Model Equation [52]

$$x_i^t = x_i^t - \alpha \{\nabla(f_i x_i^t)\} + \gamma \sum_{j \in N_i} w_{ij} [x_i^t - x_j^t] \Phi_{ij} \quad (1)$$

Where  $x_i^t$  is the state variable (for example energy allocation, scheduling weight)

Energy-aware coupling factor  $\Phi_{ij}$ : [53]

$$\Phi_{ij} = \frac{E_i^{res} + E_j^{res}}{2E_{max}} \cdot \frac{1}{1 + \gamma L_{ij}} \quad (2)$$

$E_i^{res}$  Signifies residual energy of node  $i$ ,  $E_{max}$  is the maximum initial energy,  $L_{ij}$  Denotes link cost such as interference, delay, and distance, and  $\gamma$  defines tunable bias factor. Equation (2) allows consensus not to depend only on neighbor state but also to join energy balance and transmission cost.

Role-adaptability

$$w_{ij} = \frac{r_i + r_j}{2} \cdot \frac{1}{d_{eg(i)}} \quad (3)$$

$r_i = 1$  if node  $i$  is a cluster head, otherwise zero degree (avoids overload)

Objective-driven local gradient

This allows cluster heads to drive consensus more strongly, but influence decays where each node reduces a composite local objective [55]

$$f_i(x_i) = \alpha_1 \frac{1}{E_i^{res}} + \alpha_2 d_{i,sink} + \alpha_3 R_i \quad (4)$$

Where  $\frac{1}{E_i^{res}}$  defines penalizes low-energy nodes,  $d_{i,sink}$  is the distance to sink, that is communication cost, and  $R_i$  Role penalty, that is, avoid repeated choosing of CH. Figure 2 is the flowchart illustrates a hybrid consensus-driven decision-making framework that integrates node state monitoring, intelligent optimization, and adaptive control to achieve dynamic energy balancing and extended lifetime in heterogeneous wireless sensor networks.

The sequence initiates from the network's overall size (N), it progresses to clustering (K), initiates residual energy  $E_i^{res}$  and transmission energy  $E_i^{trans}$ , optimizes the objective function  $P_{obj}$ , advances to consensus or routing selection, and ultimately concludes the process.

The consensus optimization series of mathematical models offers a systematic structure for analyzing energy usage, transmission efficiency, and optimization trade-offs in HWSNs. By incorporating consensus optimization, clustering dynamics, and energy-aware routing into model equations, the formulations reflect interactions at both the individual sensor node scale and the overall network operation. Collectively, these models not only link theoretical analysis with practical deployment but also provide an extensible tool for improving efficiency, reliability, and network lifetime in multi-tier heterogeneous wireless sensor networks.

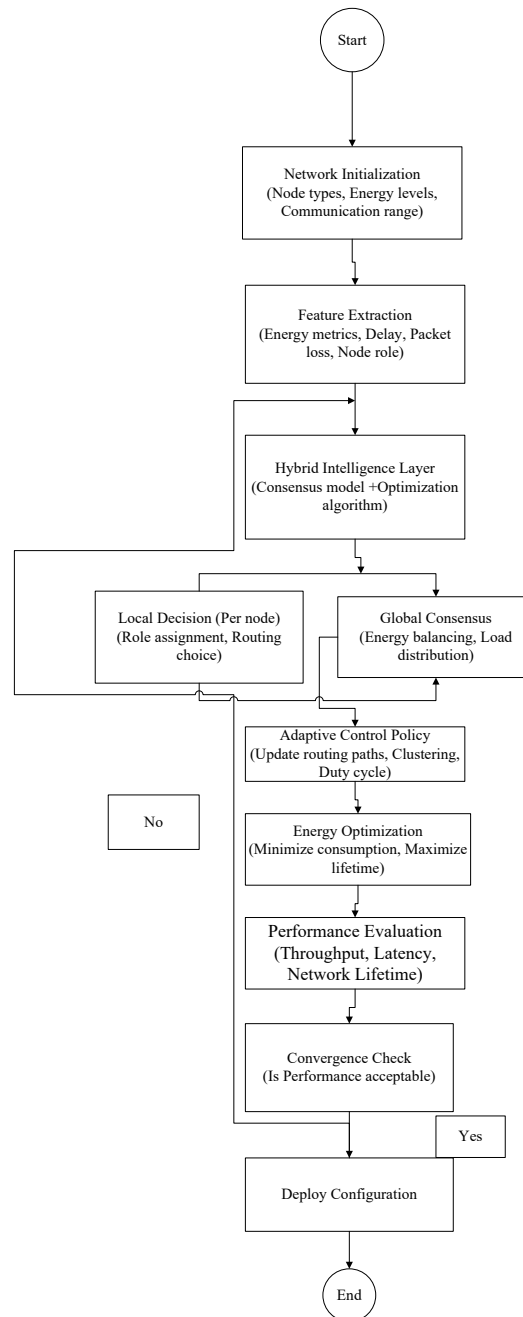


Figure 2: A Flow chart of a hybrid consensus-driven decision-making framework

#### 4.2. Role in Distributed Decision-Making and Energy Balancing

In practice, energy balancing is achieved through *weighted consensus*, where each node assigns a weight proportional to its residual energy and communication capacity. Nodes with higher residual energy exert greater influence during consensus updates, while energy-depleted nodes gradually reduce their participation. Through iterative residual energy-based averaging, routing and clustering decisions converge toward solutions that preferentially allocate heavier tasks (e.g., cluster head roles or long-range transmissions) to stronger nodes, thereby preventing early node failures and equalizing energy consumption across the network.

#### 4.3. Benefits for Multitier and Multi-Hop Communication

Consensus optimization is particularly relevant in multi-tier and multi-hop designs commonly used in heterogeneous wireless sensor networks. In multi-tier networks, nodes at different hierarchical levels must collaboratively forward aggregated packets toward the sink. Similarly, in multi-hop networks, intermediate nodes cooperate to identify routes that optimize both energy usage and communication reliability. Unlike heuristic routing schemes, which typically rely on predefined rules or local node metrics and may fail to adapt

dynamically to network changes, consensus-based approaches enable nodes to reach distributed agreements on relay selection, transmission scheduling, or load balancing in a fully decentralized manner. This collective decision-making not only reduces the risk of suboptimal routing choices inherent in heuristic methods but also minimizes communication overhead compared to frequent centralized computations. Consequently, consensus mechanisms provide superior scalability, robustness, and adaptability particularly in large-scale, energy-constrained deployments where heuristic strategies often struggle to maintain optimal performance [43].

## 5. CONSENSUS OPTIMIZATION TECHNIQUES FOR ENERGY EFFICIENCY IN HWSNs

Consensus optimization offers an integrated approach for guiding heterogeneous sensor nodes differing in energy, computation, and communication capabilities toward energy-aware decisions while ensuring scalability and robustness. In HWSNs, managing such heterogeneity is central to sustaining network lifetime, throughput, and reliability. A range of consensus-driven strategies has been applied to clustering, routing, and load management, often leveraging node-specific capabilities. This section highlights the main categories of these techniques, complemented by mathematical models and case studies [44].

### 5.1. Clustering-Based Consensus

Clustering is widely used in heterogeneous wireless sensor networks to minimize transmission cost and structure sensor nodes hierarchically. Consensus optimization enhances clustering by allowing sensor nodes to collaboratively determine CHs and member node assignments [45]. The following will be briefly highlighted to ensure that this subsection is understood: hybrid clustering consensus and weighted CH selection.

#### Hybrid Clustering Consensus

Sensor nodes combine both local metrics, such as node degree, residual energy and global coordination terms, to determine CHs. A proposed hybrid Energy-Role-Hierarchical Consensus Model is given in equation (5) and is defined as the update rule that allows each node  $i$  to adapt to its state by coupling local energy-aware gradient from with neighbor-based consensus, cluster-level management, and adaptive stochastic perturbation, hence improving energy balance and convergence in HWSNs [46]-[50].

$$x_i^{t+1} = x_i^t - \alpha_t \left( \frac{E_{max}}{E_i^{res} + \epsilon} \right) \nabla f_i(x_i^t) - \gamma \sum_{j \in N_i} I_{ij}^t w_{ij} \Phi_{ij}^t (x_i^t - x_j^t) - \mu (x_i^t - y_{ci}^t) + \eta_t \xi_i^t \quad (5)$$

where  $x_i^t$  is node  $i$  local decision at iteration  $t$ , such as transmit weight, CH score,  $\nabla f_i x_i^t$  defines the local gradient of node  $i$  utility, such as delay/energy tradeoff,  $\alpha_t$  signifies the step size that can decay with  $t$ ,  $E_i^{res}$  denotes residual energy of node  $i$ :  $E_{max}$  is the maximum initial energy:  $\epsilon$  small positive constant to avoid division by zero. Energy-scaled local step: products of the gradient step by  $\frac{E_{max}}{E_i^{res} + \epsilon}$  so limited energy nodes take smaller local steps (conservative) while resource-rich nodes move more aggressively.  $\gamma$  is the base consensus coupling strength.  $N_i$  signifies neighbor set of nodes  $i$ ,  $I_{ij}^t \in \{0, 1\}$  is sparsification indicator: 1 if neighbor  $j$  is among a selected top- $k$  contributors at time  $t$  (minimize communications) : Selection can be based on  $|x_i^t - x_j^t| \Phi_{ij}^t$  or  $top - k \Phi_{ij}^t$ .  $w_{ij}$  Is normalized link weight (row stochastic).  $\Phi_{ij}^t$  Signifies energy-role-link coupling factor

$$\Phi_{ij}^t = \frac{E_i^{res} + E_j^{res}}{2E_{max}} \cdot \frac{Rel_{ij}^t}{1 + \lambda L_{ij}} \cdot (1 + \rho |r_i^t - r_j^t|) \quad (6)$$

$L_{ij}$  is link cost like distance, delay, and path-loss.  $Rel_{ij}^t$  Denotes measured link reliability,  $r_i^t \in [0, 1]$ : Role score, such as the likelihood of being CH,  $\rho$  boosts coupling when role vary to accelerate agreement across roles boundaries. This allows the consensus term adapt to energy, link quality, and role differences.  $\mu$  is hierarchical inter-level coupling weight,  $y_{ci}^t$  Denotes cluster / super-node state for the cluster  $c(i)$  containing node  $i$ ; these  $y_k^t$  are themselves updated by a small-dim consensus among CHs.  $\eta_t \xi_i^t$  is stochastic perturbation:  $\xi_i^t$  is zero-mean noise for escaping poor local minima and encouraging exploration.

#### Weighted CH Selection

The derivative of role probability is [56]:

$$p_i = \sigma(k(U_i - T)), r_i = 1(p_i > \rho) \quad (7)$$

where  $\sigma(.)$  defines the sigmoid function, allowing a smooth transition between normal nodes and CHs. This stops overloading nodes with limited energy.

### 5.2. Transmission Strategies in Consensus [57][58]

Consensus can direct the choice of routing paths by balancing between direct, multi-hop, and adaptive strategies. Direct Transmission: nodes send data to CH or sink if the remaining energy of the sensor node is above the threshold as follows

$$E_i^{res} > E_{th}. \quad (8)$$

Multi-hop Transmission: forwarding nodes are iteratively solved by using equation (9):

$$x_i^{t+1} = x_i^t - \alpha[\nabla f_i(x_i^t) + \gamma \sum_{j \in N_i} w_{ij} (x_i^t - x_j^t)] \quad (9)$$

where  $f_i(x_i)$  encodes energy-distance cost. Adaptive Routing: Combines congestion, distance, and the node's remaining energy into the update weight as follows

$$w_{ij} = \frac{\exp(-\lambda L_{ij})}{\sum_{k \in N_i} \exp(-\lambda L_{ik})} \cdot \frac{E_i^{res}}{E_{max}} \quad (10)$$

This equation (10) ensures routing decisions adjust dynamically to local energy circumstances.

### 5.3. Load Balancing and Weighting Mechanisms

Consensus updates can be improved to integrate load-balance weights, allowing equitable resource usage using equation (11):

$$x_i^{t+1} = x_i^t + \varepsilon \sum_{j \in N_i} \left( \frac{E_j^{res}}{\deg(j)} - \frac{E_i^{res}}{\deg(i)} \right) \quad (11)$$

This rule penalizes overloaded cluster heads or sensor nodes with many neighbors, allocating workload proportionately to available energy. The proposed hybrid energy role hierarchy consensus model integrates energy-sensitive adaptation with hierarchical organization, providing a scalable approach to reduce imbalance in HWSNs. Its distinct contribution is the consolidation of gradient descent, weighted consensus, and role coordination into a unified framework. This innovation presents a new direction for extending network lifetime and advancing consensus-based protocol design [67][68].

### 5.4. Consensus in Multi-Tier Architectures

Heterogeneous sensor networks commonly adopt multi-tier frameworks with low-energy sensor nodes, CHs, and super cluster heads. Consensus optimization improves coordination across these tiers. Intra-cluster consensus aligns CHs/Super Cluster Heads (SCHs) is derived as follow

$$x_i^t = x_i^t + \varepsilon \sum_{j \in C_k} x_j^t - x_i^t \quad (12)$$

Where  $C_k$ , defines the k-th cluster. Inter-cluster consensus coordinates CHs / Super Cluster Heads (SCHs) to global objectives is described as

$$y_k^{t+1} = y_k^t - \alpha \nabla F_k(y_k^t) + \gamma \sum_{l \in N_k} y_l^t - y_k^t \quad (1)$$

Where  $y_k$  defines the state of cluster k, and  $F_k$  is its energy-traffic model. The combination of hybrid clustering consensus, weighted cluster-head selection, and optimized transmission methods significantly improves energy efficiency and communication reliability in wireless sensor networks. Through the use of load balancing and adaptive weighting schemes, the framework prevents exploitation on individual nodes and extends overall network longevity. In addition, applying consensus within a multi-tier architecture enables scalable coordination and strengthens network robustness, establishing a comprehensive approach for sustainable and effective operation [69][70].

While consensus optimization improves coordination and energy-aware decision making in heterogeneous wireless sensor networks, its computational complexity can introduce non-negligible energy overhead. In resource-constrained sensor nodes, iterative consensus algorithms require repeated local computations and frequent message exchanges, both of which consume processing power and communication energy. As network size increases, the complexity typically grows with the number of nodes and iterations needed for convergence, potentially offsetting the energy savings achieved through optimized routing or clustering. Therefore, practical consensus models must balance solution accuracy with computational simplicity, favoring lightweight algorithms and localized updates to ensure that the energy cost of computation does not exceed the energy gains provided by consensus.

### 5.4. Impact of Byzantine Attacks on Energy Consensus

In energy consensus-based heterogeneous wireless sensor networks, Byzantine nodes either compromised or malicious can deliberately transmit false state information, such as incorrect residual energy levels or routing

metrics. This behavior disrupts the consensus process by biasing collective decisions, leading to inefficient relay selection, unbalanced load distribution, and premature energy depletion of honest nodes. As a result, network lifetime and reliability are significantly degraded, and the convergence of consensus algorithms may be delayed or entirely prevented. Therefore, without robust fault-tolerant mechanisms, Byzantine attacks can negate the energy benefits of consensus optimization and threaten the stability of the overall network.

### 5.5. Case Studies of Algorithms Adapted with Consensus

Consensus optimization has been progressively incorporated into traditional clustering and routing schemes to enhance energy performance in heterogeneous wireless sensor networks (HWSNs). Well-known protocols like LEACH and DEEC, though widely utilized, encounter challenges in achieving balanced energy usage and maintaining scalability in heterogeneous settings. Embedding consensus mechanisms into these frameworks enables more efficient role rotation, equitable load sharing, and greater network stability.

#### LEACH and Variants:

In its original form, LEACH relies on random cluster-head (CH) assignment, which can result in unbalanced energy depletion. Consensus-based adaptations enable nodes to iteratively share residual energy and distance metrics with their neighbors before CH selection. Through distributed averaging, this approach yields more stable elections, lowers the risk of early node depletion, and ensures a fairer distribution of workload [51][52].

#### DEEC

DEEC determines cluster-heads (CHs) by comparing each node's residual energy with the network's average, which makes it effective in heterogeneous settings. With consensus integration, DEEC enables local coordination among nodes to fine-tune CH selection and routing, minimizing energy disparities and prolonging network lifetime. Additionally, consensus-based weighting helps alleviate congestion around nodes with higher energy reserves [53].

#### Other Protocols (example given: TEEN, SEP, Hybrid approaches)

Protocols such as TEEN, which relies on threshold-based reporting, and SEP, developed for stable clustering in heterogeneous settings, gain efficiency when enhanced with consensus via adaptive weighting and neighbor coordination. Likewise, hybrid models that integrate meta-heuristic techniques (example given: PSO, GA, or GWO) with consensus updates achieve quicker convergence and stronger resistance to energy imbalance [54].

These modifications illustrate that consensus optimization can evolve conventional algorithms into more resilient and energy-efficient approaches. Through the integration of distributed coordination and load-balancing mechanisms, consensus-based protocols surpass their traditional counterparts in extending network lifetime, ensuring fairness, and supporting scalability, essential attributes for next-generation HWSN deployments. Table 3 shows the comparison of the most recent work done in WSNs, and also Figure 3 shows critical analysis of energy efficiency and consensus models in HWSNs

Figure 3 illustrates the critical analysis of energy efficiency and consensus models HWSNs. From Table 3, Energy Efficiency, HWSNs, and Critical Comparative Analysis demonstrate a moderate representation of approximately~67%. Conversely, Comprehensive Integration and the Novel Hybrid Energy Role Hierarchy Consensus are completely lacking (0%), highlighting the most significant research gap.

A comparison of previous research work in this field is shown in Table 3. While most researchers focused on energy efficiency and heterogeneous wireless sensor networks, they paid little attention to the followings: comprehensive integration of consensus and energy model thereby bridging clustering, routing and load-balancing technique, formulation of novel hybrid energy role hierarchy consensus hence combines energy-aware gradient descent, consensus weighting, and hierarchy management to improve distributed optimization, and critical analysis of the existing approaches to highlights improvements in scalability, fairness, and energy balance. This review article has filled this gap.

Note: ✓ depicts present ✕ Signifies absent.

Table 3 Comparison of the most recent work done in WSNs

| Ref  | Energy Efficiency | HWSNs | Comprehensive Integration of Consensus and Energy Models | Formulation of a Novel Hybrid Energy Role Hierarchy Consensus | Critical Comparative analysis of existing approaches | Identification of core challenges and research gap.                |
|------|-------------------|-------|----------------------------------------------------------|---------------------------------------------------------------|------------------------------------------------------|--------------------------------------------------------------------|
| [58] | ✓                 | ✓     | ✕                                                        | ✕                                                             | ✕                                                    | Lack of novel Hybrid Energy Role Hierarchy Consensus Models hence, |

| Ref  | Energy Efficiency | HWSNs | Comprehensive Integration of Consensus and Energy Models | Formulation of a Novel Hybrid Energy Role Hierarchy Consensus | Critical Comparative analysis of existing approaches | Identification of core challenges and research gap.                                                    |
|------|-------------------|-------|----------------------------------------------------------|---------------------------------------------------------------|------------------------------------------------------|--------------------------------------------------------------------------------------------------------|
|      |                   |       |                                                          |                                                               |                                                      | leads to more energy consumption                                                                       |
| [59] | ✓                 | ✓     | ×                                                        | ×                                                             | ✓                                                    | Lack of novel Hybrid Energy Role Hierarchical consensus Models hence, leads to more energy consumption |
| [60] | ✓                 | ✓     | ×                                                        | ×                                                             | ×                                                    | Lack of novel Hybrid Energy Role Hierarchy Consensus Models hence, leads to more energy consumption    |
| [61] | ✓                 | ×     | ×                                                        | ×                                                             | ×                                                    | Lack of novel Hybrid Energy Role Hierarchy Consensus Models hence, leads to more energy consumption    |
| [62] | ✓                 | ×     | ×                                                        | ×                                                             | ×                                                    | Lack of novel Hybrid Energy Role Hierarchy Consensus Models hence, leads to more energy consumption    |
| [63] | ✓                 | ×     | ×                                                        | ×                                                             | ×                                                    | Lack of novel Hybrid Energy Role Hierarchy Consensus Models hence, leads to more energy consumption    |
| [64] | ✓                 | ×     | ×                                                        | ×                                                             | ×                                                    | Lack of novel Hybrid Energy Role Hierarchy Consensus Models hence, leads to more energy consumption    |
| [65] | ✓                 | ×     | ×                                                        | ×                                                             | ×                                                    | Lack of novel Hybrid Energy Role Hierarchy Consensus Models hence, leads to more energy consumption.   |
| [66] | ✓                 | ×     | ×                                                        | ×                                                             | ×                                                    | Lack of novel Hybrid Energy Role Hierarchy Consensus Models hence, leads to more energy consumption.   |

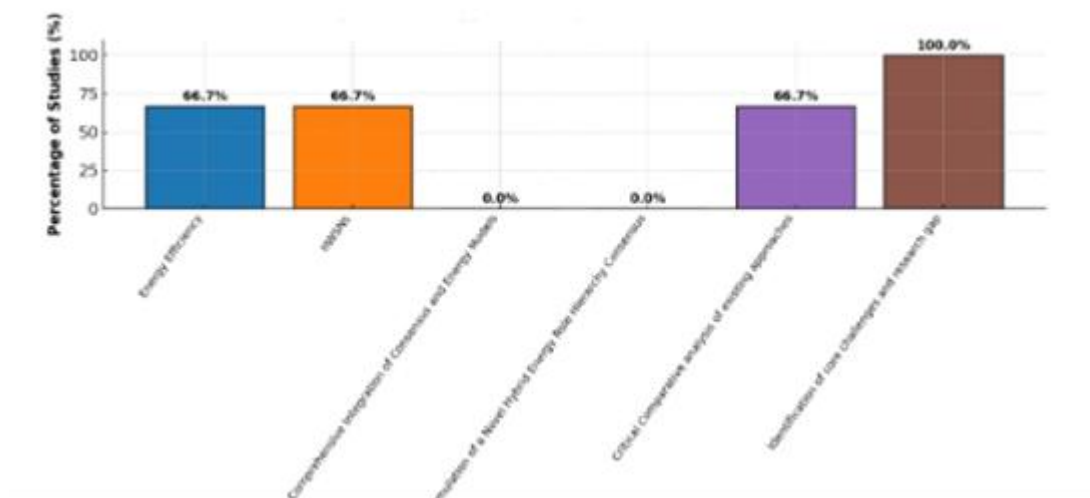


Figure 3: Critical analysis of energy efficiency and consensus models HWSNs

## 5. OPEN RESEARCH CHALLENGES

While consensus optimization has emerged to be an effective strategy for enhancing energy efficiency in heterogeneous wireless sensor networks, its broader applicability in large-scale and real-world scenarios remains constrained by several unresolved issues. These limitations arise from the growing complexity of IoT infrastructures, frequent changes in node behavior, and the integration of intelligent control and renewable energy sources.

### 5.1. Scalability to Ultra-dense IoT networks

The rapid expansion of IoT devices introduces major scalability challenges for consensus-based algorithms. Conventional consensus methods often struggle as node density increases because frequent message exchanges lead to high communication overhead, slower convergence, and network instability. These limitations arise from the difficulty of maintaining synchronized state across thousands of densely deployed nodes using flat, fully distributed protocols. To address this, future approaches should leverage hierarchical, clustered, or probabilistic consensus structures that reduce synchronization costs while preserving effective global coordination in ultra-dense environments.

### 5.2. Consensus under Dynamic Topologies and Mobility

In practical deployments, HWSNs often encounter node mobility, failures, and variable connectivity conditions. Conventional static consensus models are unable to adapt effectively to such dynamic network variations. Hence, designing topology-aware and mobility-aware consensus mechanisms capable of preserving stability, ensuring reliable communication, and rapidly adapting to network changes remains a key challenge for achieving resilient performance.

### 5.3. Security and Fault-tolerant Consensus in HWSNs

Because consensus algorithms depend on inter-node cooperation and information sharing, they are vulnerable to malicious activity, communication errors, and falsified data. Incorporating efficient yet robust fault-tolerance mechanisms in energy-limited HWSNs remains a difficult task. Future studies should aim to develop secure consensus models that integrate trust metrics, anomaly detection, and block-chain-based validation to preserve reliability and data integrity while minimizing computational overhead.

### 5.4. Integration with AI /ML for Predictive Optimization

Integrating AI and machine learning with consensus optimization offers a promising route for achieving intelligent and adaptive energy management. Despite its potential, this integration is still in its early stages. Future frameworks should employ predictive learning methods like reinforcement or federated learning to forecast network conditions, dynamically adjust consensus parameters, and autonomously enhance energy usage and communication efficiency. This fusion can evolve traditional consensus models into adaptive, context-aware decision-making systems.

### 5.5. Consensus under Energy Harvesting and Renewable-powered WSNs

The development of energy-harvesting and renewable-powered sensor networks has brought about uneven and time-varying energy availability across nodes. Developing consensus mechanisms that can flexibly adjust to these fluctuations while ensuring fairness and convergence remains a significant research hurdle. Future solutions should incorporate energy forecasting techniques and adaptive weighting strategies to achieve balanced performance between energy-harvesting and battery-dependent nodes. Addressing these unresolved challenges will pave the way for a new generation of consensus-driven energy optimization frameworks capable of achieving sustainable scalability, robustness, and intelligence in heterogeneous WSNs. Future research should focus on bridging theoretical consensus formulations with adaptive, secure, and energy-efficient architectures tailored to real-world IoT environments.

## 6. CONCLUSION

Consensus optimization offers a transformative framework for improving energy-efficient management in heterogeneous wireless sensor networks (HWSNs). By integrating distributed decision-making, adaptive weighting strategies, and hierarchical organization, consensus-based models effectively address long-standing issues of energy imbalance, scalability, and reliability under heterogeneous and dynamic conditions. The reviewed models and methodologies highlight how consensus mechanisms can significantly improve network longevity, load fairness, and operational stability in heterogeneous and dynamic environments. However, fully realizing these potential requires connecting theoretical models with real-world applications that leverage AI-based prediction, secure communication schemes, and renewable energy utilization. Ultimately, consensus

optimization provides a cohesive and intelligent foundation for advancing future HWSNs, fostering sustainable and efficient operation within evolving IoT and smart infrastructure ecosystems.

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