Optimized Energy-Efficient Knapsack Algorithm for Intelligent Cluster Head Selection in Wireless Sensor Networks

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ABSTRACT

Wireless Sensor Networks (WSNs) are vital for data collection, monitoring and environmental analysis. This study presents a new energy balancing method that uses a Cluster Head (CH) selection policy based on the residual energy state of nodes, involving uniform distribution of energy consumption, with the aim to increase network lifespan and performance. Calculations are performed with the Knapsack method, which considers energy constraints and optimizes resource allocation. Performance tests with NS2.34/2.35 show significant improvements. Important findings are the extended network longevity, with the proposed solution increasing network lifetime by 16%, increased data usage by 17%, reduced latency by 14%, improved coverage by widening the monitored locations by 20%. These findings show that the proposed energy-balancing algorithm can be used to increase the lifetime and performance of WSNs. This work contributes to the ongoing effort to improve WSN performance and sustainability, particularly in circumstances when energy efficiency is essential.

Keywords-Cluster Head (CH) selection; energy efficiency; energy management; Knapsack algorithm; WSN

I. INTRODUCTION

Wireless Sensor Networks (WSNs) are commonly utilized nowadays, but face challenges such as limited energy, communication reliability, dynamic topology, and scalability constraints. To address these, a Knapsack Algorithm-enabled Smart Cluster Head (CH) Selection strategy is proposed, focusing on optimizing energy usage, adapting to dynamic network conditions, ensuring scalability for large deployments, and extending network lifespan. This approach improves traditional random and heuristic-based CH selection methods, which often fail to maximize energy efficiency or network longevity. The proposed method will be evaluated on metrics such as energy efficiency, network reliability, and scalability, demonstrating its effectiveness in enhancing WSN performance and lifespan. This strategy offers a holistic solution to WSN challenges, providing valuable insights for improving network efficiency in real-world applications.

Several approaches aim to conserve energy in WSNs. They are categorized into energy-efficient measures, clustering techniques, and data aggregation methods. Protocols like LEACH (Low Energy Adaptive Clustering Hierarchy) and TEEN (Threshold-sensitive Energy Efficient Sensor Network Protocol) focus on optimizing communication channels. Clustering methods such as HEED (Hybrid Energy-Efficient Distributed) and PEGASIS (Power-Efficient Gathering in Sensor Information Systems) enhance network lifetime by forming efficient clusters [1, 2]. Data aggregation techniques, like SPAN (Sensor Protocols for Aggregation in Sensor Networks), further reduce energy consumption during data transmission [3]. Despite these advancements, challenges persist. Most methods lack an integrated approach combining clustering and routing algorithms effectively [4]. Additionally, adapting to the dynamic nature of WSNs changing network conditions and node failures remains a significant hurdle in sustaining energy-efficient configurations over time [5].

The proposed Smart Cluster Head Selection technique leverages the Knapsack Algorithm to overcome limitations in existing approaches. This algorithm facilitates intelligent and optimized cluster head selection by considering energy constraints and communication needs [6]. By integrating clustering and routing decisions, the network adapts dynamically to changing conditions, optimizing energy usage while ensuring efficient data transmission paths [7]. This approach balances energy distribution among sensor nodes, enhancing network longevity [8]. The literature review considered the recent advancements in these techniques, studying methodologies, benefits, limitations, and potential research areas. It explores optimization algorithms designed to extend the lifespan of WSNs, evaluating robustness, weaknesses, and trade-offs in current approaches. Such insights pave the way for designing high-performance, long-range wireless sensor networks [9]. Energy-efficient routing and clustering are critical for WSNs, with cluster heads playing a central role in data collection [10]. Comparative evaluations of proposed methods against existing performance metrics highlight their effectiveness [6]. However, challenges such as the overloading of certain CHs, leading to rapid energy depletion, remain [11]. Efficient load balancing is crucial in WSNs and requires advanced clustering and routing methods. Optimization techniques like GA, PSO, and GWO help minimize the distance between source and destination nodes [12]. Networks are divided into clusters, and to prevent rapid energy depletion, each CH is assigned a relay node [13]. Re-clustering occurs only when 50% of the current cluster heads' energy is exhausted, conserving energy and prolonging network life [14]. Such strategies enhance WSN longevity and maintain proper load distribution. Clustering and routing optimization algorithms improve energy efficiency by connecting CHs to sinks through single-hop and multi-hop transmissions. This involves criteria like residual energy, CH density, and cluster distribution [15].

Despite the progress, gaps remain in integrating clustering and routing algorithms and maintaining optimal configurations in dynamic environments [16]. The proposed Smart Cluster Head Selection strategy using the Knapsack Algorithm addresses these gaps. By dynamically optimizing CH selection, it ensures balanced energy usage, adapts to changing conditions, and maintains efficient data paths [17]. Unlike GA, PSO, and GWO, which face challenges like poor convergence and scalability, the Knapsack Algorithm provides simplicity, lower computational overhead, and better adaptability for energy-critical scenarios [18]. This strategy offers a holistic solution for energy conservation in WSNs, improving performance and extending network lifespan [19]. Detailed evaluations and comparisons in subsequent sections will showcase its effectiveness in enhancing energy efficiency and overall network longevity [20].

II. THE PROPOSED MODEL

A. System Overview

The approach for applying the Knapsack Algorithm to select CHs in WSNs focuses on enhancing energy efficiency through strategic CH selection. This process considers factors such as remaining energy, communication costs, and node distance. The technique involves a series of steps that outline the comprehensive strategy:

B. Problem Formulation

The CH selection process is modeled as a 0/1 Knapsack Problem, where the goal is to maximize network lifetime by selecting CHs that minimize energy consumption. The problem is defined as:

Objective Function: Maximize the network's overall energy efficiency, which is formulated as in (1):

$$\text{Maximize} \quad \sum_{i=0}^{n} \mathrm{Ei} * \mathrm{xi} \tag{1}$$

where E_i represents the residual energy of the i^{th} sensor node, xi is a binary decision variable that returns 1 if node i is picked as a CH and 0 otherwise.

C. Constraint

- Energy Constraint: CHs should have sufficient residual energy to handle both intra and inter-cluster interaction.
- Overhead Communication: Redundant connections are eliminated to reduce power consumption.
- Cluster Size Limitation: Each CH can support only a limited number of nodes, avoiding overburdening.
- Knapsack Constraint: Total energy consumption by the selected CHs should not exceed the network's energy budget.

D. Knapsack Algorithm for CH Selection

To solve the CH selection problem, the Knapsack Algorithm is implemented. The process follows these steps:

- Initialization: Each node calculates its remaining energy, the distance to other nodes, and the distance to its base station.
- Candidate CH selection: Based on remaining energy and proximity, nodes with more energy and closer to the base station are selected as potential CHs.
- Knapsack Formulation: The algorithm evaluates each candidate CH using a Knapsack approach, considering:
  - Weight: The energy consumption and communication overhead for each node.
  - Value: The node's residual energy.
- Selection Process: Nodes with the highest value-to-weight ratio are selected as CHs. The algorithm ensures that the total weight (energy consumption) does not exceed the predefined limit (network energy constraint).

E. Cluster Formation

Once the CHs are selected, the remaining sensor nodes are clustered based on proximity and signal strength. Each node calculates its distance from the nearest CH and is assigned to the cluster controlled by the CH that requires minimal energy for communication.

F. 2.5 Data Aggregation and Transmission

- Inter-cluster communication: Each node transmits its data to its CH. The CH aggregates data from all cluster members, thereby reducing redundant data transmission.
- Inter-cluster communication: CHs transmit appropriate data to the base station either directly or through multi-hop routes depending on distance and energy constraints.

G. Energy Consumption Model

The energy consumption model follows the first-order radio model:

- Transmission Energy (Etx): Is the energy required to transmit data from node i to CH j:

$$E_{tx}\ (i, j) = E_{elec} \times d_{ij} \qquad (2)$$

where E_{elec} represents the energy consumed per bit for operating the radio components, while d_{ij} denotes the spatial separation between node i and cluster head j.

- Reception Energy (E_{rx}): Is the energy consumed by the CH to receive data from a member node:

$$E_{rx} = E_{elec} \qquad (3)$$

- Aggregation Energy (E_{agg}): Each CH consumes energy for data aggregation before transmitting to the base station, as expressed by:

$$E_a = E_{DA} \times n \qquad (4)$$

where E_{DA} is the data aggregation energy per bit, and n is the number of bits received.

H. WSN Knapsack Algorithm for Cluster Head Selection

The process begins with node deployment, followed by the initialization phase, where a set of potential CH candidates is identified, each associated with specific costs and values. Subsequently, data are collected and pre-processed to facilitate analysis. The problem is then formulated as a Knapsack problem aimed at maximizing the total value of selected CHs while adhering to given constraints. A fitness function is developed to evaluate the performance of each potential CH configuration, ensuring optimal selection. Figure 1 illustrates the workflow for CH selection.

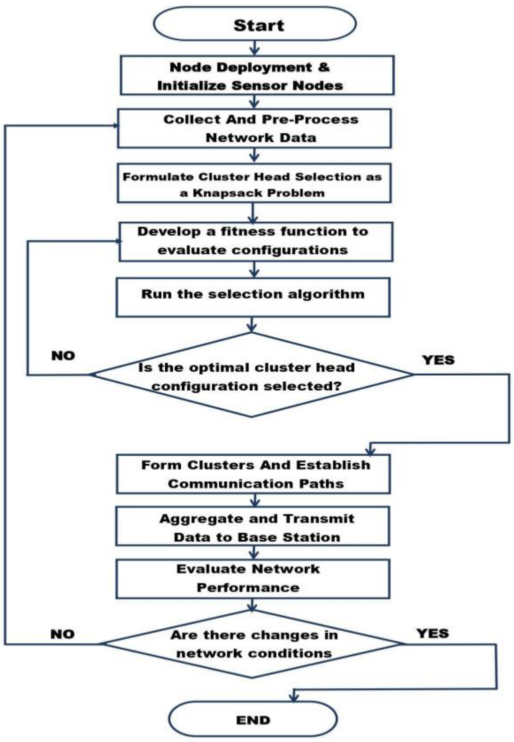

Fig. 1. Workflow of the the optimized energy-efficient Knapsack algorithm.

I. The Proposed Algorithm

The amount of energy needed to process a packet $e(p_i)$ through an active intermediate node is:

$$e(p_i) = (E_r + E_{da} + E_t) \qquad (5)$$

where E_r, E_{da}, and E_t are the energy requirements for receiving, aggregation, and transmission of the packet, respectively.

The remaining energy (E_{res}) of a node after packet processing (pi) is provided by (6):

$$E_{res} = E - e(p_i) \qquad (6)$$

Thus, the best number of packets handled from an intermediate node is found within the restrictions of available energy. This is accomplished through the use of a multi-objective optimization approach that uses a multi-objective array L[I, E] to compute the optimized packets handled by the intermediate node. The flowchart detailing the CH selection process can be seen in Figure 2, while the algorithmic steps are shown below.

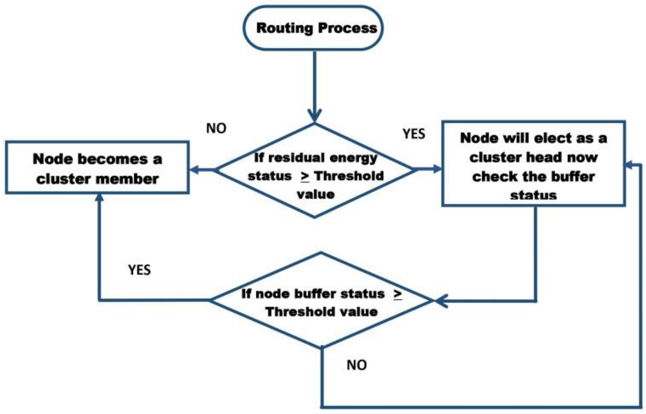

Fig. 2. Flow chart of CH selection.

Knapsack Algorithm to Compute Node Residual Energy

1. Start
2. Calculating parameters Node Residual Energy is used for high packet forwarding paths.
3. $(E, E_{res}, e(P_i))$
4. Packet must in process == true
5. If $(E_{res} \geq e(P_i))$
6. Compute $(CRS = Eres - e(P_i))$
7. If $(CRS \geq CR_{Thmax})$
8. Involve the Node in the Routing Process
9. Else Node cannot take part in the routing procedure.
10. End

This research project attempts to address the issues of sustainable wireless networks using sensors by applying new optimization techniques based on routing and clustering. The main objective is to create energy efficient routes and scalable enough to increase network lifetime without degrading performance. The aim of this study is to contribute new strategies on the improvement of the energy efficiency and lifetime of WSNs.

III. SIMULATION SETUP

Table I shows the specifications of the carried out simulation to assess the efficacy of the suggested knapsack method for optimum CH selection. The simulations were performed in NS2.34/2.35. The network topology was defined as a two-dimensional 300 m × 300 m area, which represents a typical deployment scenario for WSNs. A total of 100 sensor nodes were randomly deployed within the defined area. Each node had a unique initial energy level, drawn from a uniform distribution between 0.5 J and 1.5 J to simulate variability in energy availability.

TABLE I. SIMULATION SPECIFICATIONS

Parameter	Description
Nodes (Numbers)	100
Channel Type	Wireless
Received Power	1 mw
Transmitted Power	2 mw
Packet Size	1000 bits
Area (m)	300 m ×300 m

IV. SIMULATION RESULTS

The simulation results of the proposed Energy-Efficient Knapsack Algorithm demonstrate significant improvements in WSN performance. The algorithm extends network lifetime by 16%, increases data throughput by 17%, and reduces latency by 14%, ensuring efficient data utilization. Additionally, it achieves uniform energy consumption, reducing overall energy usage by 12%, and enhances network coverage by 20%. These findings confirm the effectiveness of Knapsack in optimizing energy efficiency, prolonging network lifespan, and improving overall WSN reliability.

A. Network Lifetime

Figure 3 illustrates that the knapsack-based CH selection extends network lifetime by 16–32% compared to PSO, GA, and GWO. This improvement stems from selecting CHs based on remaining energy, ensuring nodes with higher energy levels manage clusters, preventing premature CH failure, and stabilizing the network. GWO's modest improvement is attributed to its ability to balance energy consumption across nodes, avoiding localized depletion.

B. Energy Consumption

Figure 4 illustrates that the total energy consumption in the network is reduced by 14 to 20%. This reduction is attributed to the intelligent CH selection process that minimizes communication overhead by selecting CHs that are closer to their member nodes, thereby reducing the transmission distance and energy usage. The hybrid approach of using the knapsack model ensures that energy is used more efficiently, and CHs are selected in such a way that data transmission to the base station incurs minimal energy cost.

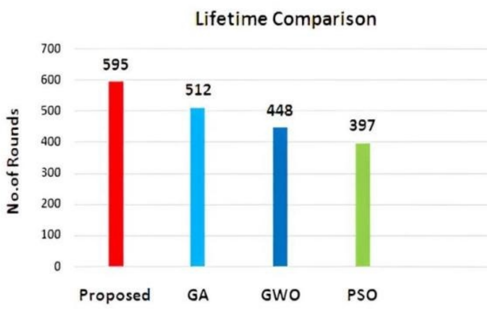

Fig. 3. Lifetime comparison.

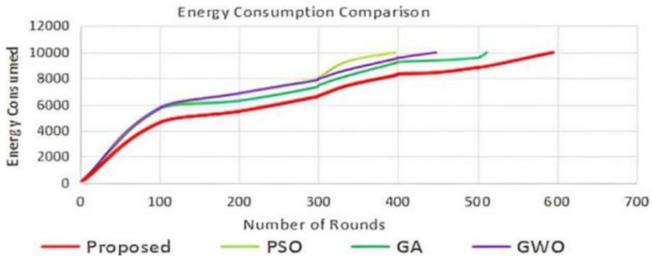

Fig. 4. Energy consumption comparison.

C. Number of Alive Nodes

Figure 5 shows that the Knapsack algorithm retains 25–35% more alive nodes compared to PSO, GA, and GWO at the 50% node mortality point, due to its balanced energy consumption strategy, evenly distributing energy usage, ensuring gradual node depletion, and preventing early network partitioning.

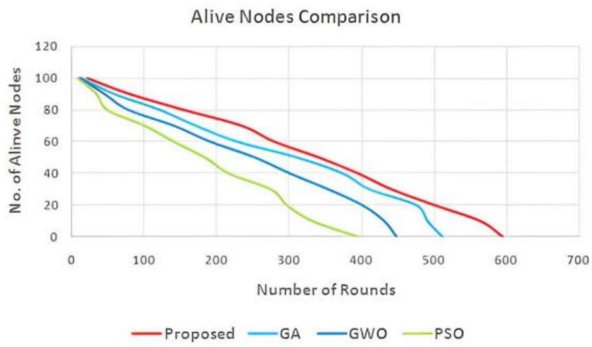

Fig. 5. Alive node comparison.

D. Overall Comparison

Table II and Figure 6 summarize the comparison results.

TABLE II. OVERALL COMPARISON OF PARAMETERS

Parameters	PSO	GA	GWO	Proposed (Knapsack)
Network lifetime (s)	397	512	448	595
Energy consumption (J)	350	360	375	300
Number of alive nodes	60%	70%	65%	88%

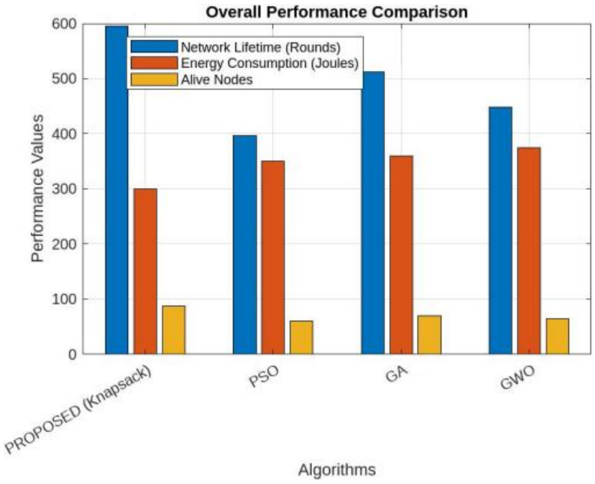

Fig. 6. Overall parameter comparison.

V. CONCLUSION

This study introduces an energy-balancing approach for Wireless Sensor Networks (WSNs) that employs a residual energy-based Cluster Head (CH) selection mechanism optimized with the Knapsack algorithm. The research method involves designing a uniform energy consumption strategy to address the inherent challenges of the limited energy resources in WSNs. The proposed method prioritizes nodes with higher residual energy for CH selection, ensuring balanced energy usage across the network. Simulations conducted in NS2.34/2.35 validate the approach's effectiveness, demonstrating a 16% improvement in network lifetime, a 17% increase in data throughput, and a 14% reduction in latency compared to traditional methods. The strategy also expands network coverage by 20%, enabling wider monitoring areas. These results underscore the algorithm's ability to optimize resource allocation, reduce data transmission delays, and extend overall network performance. The detailed evaluation of the algorithm against existing methods highlights its novelty and practical applicability in energy-constrained environments. By addressing key metrics such as energy efficiency, data reliability, and scalability, this study contributes a robust solution to the ongoing challenges in WSNs, setting the stage for future enhancements in dynamic and large-scale deployments.

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