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Energy-efficient knapsack algorithm for intelligent cluster head selection in IoT enabled wireless sensor networks

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ABSTRACT

The demand for wireless sensor networks (WSN) has grown rapidly with the development of the internet of things (IoT), which requires sensors that are both energy-efficient and scalable to support continuous data collection and real-time monitoring applications. The main challenge is limited battery life in network nodes, which necessitates effective energy management strategies to prolong network lifespan. This paper introduces an energy-efficient knapsack algorithm (EEKA) for smart cluster head (CH) selection in IoT WSNs, aiming to optimize energy use while enhancing network stability and data transmission efficiency. The approach features a CH selection strategy based on residual energy, ensuring an even distribution of energy among sensor nodes. The incorporation of the knapsack optimization technique enhances resource allocation, thereby minimizing energy consumption and maximizing transmission reliability. Simulation results using NS2.34/2.35 show remarkable improvement in performance metrics compared to existing techniques: EEKA extends the network lifetime by 16% whereas throughput is enhanced by 17% with reduced latency by 14% under efficient data distribution. Moreover, adaptive CH selection strategy extends coverage by another 20% for wider and effective monitoring. All these results therefore confirm that EEKA has successfully focused on improving energy efficiency, stability, and scalability regarding IoT-driven WSNs to make it a practical solution for real-world applications like smart cities, environmental observation, and industrial automation.

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1. INTRODUCTION

Wireless sensor networks (WSN) are crucial for internet of things (IoT) applications such as environmental monitoring, health care and industrial automation. However, their performance is interrupted by affecting the cluster head (CH) energy, disabled battery, and sub-optimal CH selection, network period and efficiency [1]. Heuristic and random CH choices often lead to unbalanced energy distribution, increased consumption, and reduced challenges of network life in scalable IoT networks [2]. Various energy-efficient clustering and routing, including LEACH and TEEN, have been suggested, which improve communication, but suffer from static clustering boundaries, causing premature node failure [3]. Adaptive protocols such as hybrid energy-efficient distributed clustering (HEED) and power-efficient gathering in sensor information systems (PEGASIS) reduce overhead, but still fail to integrate clustering with routing, causing inefficient energy use [4]. While SPAN reduces redundant transmissions, it lacks dynamic CH selection, resulting in unbalanced network load [5]. Many existing cluster and routing strategies consider these two problems separately, leading to suboptimal network performance. Genetic algorithms (GA), particle swarm optimization (PSO), and gray wolf optimizer (GWO) have been widely used to optimize the CH selection. However, these approaches, to a large extent, suffer from high calculation complexity, slow convergence, and poor scalability in the IoT network [6]. In addition, heuristically based solutions are often dependent on random search mechanisms, making them disable real-time applications where energy savings are important [7].

To overcome these limitations, this study proposes the energy-efficient knapsack algorithm (EEKA) for intelligent CH selection in IoT-enabled WSNs [8]. EEKA combines clustering and routing optimization, improving the selection of CH based on residual energy to achieve the balanced energy distribution among nodes [9]. In contrast to heuristic-based methods, EEKA is deterministic rather than stochastic, which allows finding a computationally efficient solution under strict energy constraints [10]. EEKA's main innovations are dynamic CH selection, energy-aware routing, and knapsack-based optimization. In contrast, to avoid the unnecessary overhead of periodic re-clustering for EEKA, new CHs are selected as long as 50% energy of the existing CH is exhausted, which leads to greater stability of the network [11]. Furthermore, EEKA combines clustering and routing with a two-level transmission mechanism, where both single-hop and multi-hop are employed, improving the efficiency of data transmission while reducing communication overhead [12]. Unlike GA, PSO, and GWO, which use randomized optimization techniques to select CHs, EEKA considers a constrained knapsack optimization model to compute the optimum solution for the CH selection based on residual energy, communication cost, and network topology, thus ensuring better resource allocation and energy balancing [13]. A typical WSN architecture is depicted in Figure 1, where the sensor nodes sense data, CHs aggregate data, and the base station (BS) processes and transmits data for analysis [14].

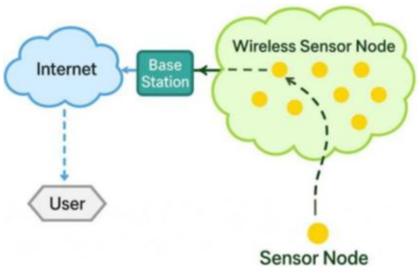

Figure 1. Depicts the basic communication method of WSN

Comparative research demonstrates that EEKA offers appreciable gains in network performance over current clustering and routing algorithms. In particular, EEKA ensures longer sensor node operation by increasing network lifetime by 16% when compared to GA, PSO, and GWO-based CH selection techniques [15]. Furthermore, it improves throughput by 17% as a result of optimized data transmission and aggregation, which results in more effective data delivery [16]. Additionally, EEKA reduces latency by 14%, enhancing WSNs' real-time communication capabilities [1]. Additionally, the algorithm enhances network coverage by 20%, which makes it ideal for use in industrial IoT, smart cities, and environmental monitoring applications [17]. Figure 2 shows different routing schemes in WSNs, emphasizing how multi-hop routing saves energy while direct transmission quickly exhausts distant nodes. In large-scale IoT deployments, EEKA improves overall efficiency, scalability, and energy utilization by combining location-based and data-centric routing strategies [18].

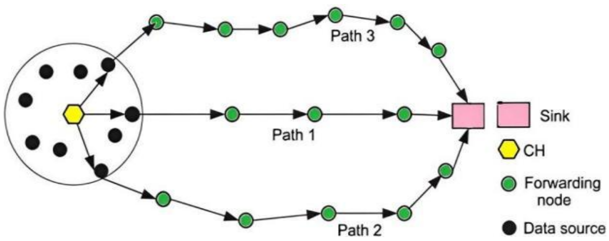

Figure 2. Illustrates several routing pathways in WSNs

Several significant advances in the field of energy-efficient WSN are made in this paper. To improve network performance, it suggests EEKA, an adaptive CH selection technique that combines routing optimization and clustering [19]. It also presents a knapsack-based CH selection model, which guarantees a load-balanced, scalable, and energy-conscious network that effectively manages the resources of sensor nodes [20]. The study highlights EEKA's capacity to optimize energy consumption and enhance data transmission by showcasing its superiority over GA, PSO, and GWO-based techniques through extensive simulations [21], [22]. Additionally, by greatly increasing network lifetime, stability, and efficiency, EEKA is a workable solution for actual IoT deployments, such as those in industrial automation, smart cities, and environmental monitoring [23].

2. THE PROPOSED METHOD

The proposed EEKA optimizes CH selection in an IoT-enabled WSN. The goal is to prolong network lifetime, reduce energy consumption, and enhance data transmission efficiency within an IoT-based architecture [24].

2.1. IoT-enabled WSN model

IoT-enabled WSN nodes allow the data to be monitored in real-time by a cloud platform. While collecting the environmental parameters and sending them through IoT gateways or fog computing nodes for later processing, these technologies ensure communication with low latency: LoRa, ZigBee, Wi-Fi, and 5G [25]. It is the BS that compiles the data to send it further to edge or cloud platforms that would improve the transmission of information, energy efficiency, and real-time accessibility for smart applications [26].

2.2. 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: maximize the network's overall energy efficiency, which is formulated as in the (1). Where x_i is a binary variable, $E_{res,i}$ is the residual energy of node i, y_j is a binary variable, C_j is the energy cost of transmission for node j and M is the total number of selected CHs.

$$\max \sum_{i=1}^{N} x_i\, E_{res,i} - \sum_{j=1}^{M} y_j C_j \tag{1}$$

Constraints:

i. Energy constraint: CHs should have sufficient residual energy to handle both intra and inter-cluster interaction as shown in (2). where $\mathrm{E_{th}}$ is the minimum required energy for a node to act as a CH.

$$\mathrm{E_{res,i}} \geq \mathrm{E_{th}},\ \forall \mathrm{i} \in \mathrm{N} \tag{2}$$

ii. Communication cost constraint: the total energy consumed for data transmission must not exceed the network's available energy as expressed in (3) where $\mathrm{E_{total}}$ is the sum of all nodes' residual energy.

$$\sum_{\mathrm{j}=1}^{\mathrm{M}} \mathrm{y_j C_j} \leq \mathrm{E_{total}} \tag{3}$$

iii. Cluster size limitation: each CH can support only a limited number of nodes, avoiding overburdening any single CH as expressed in (4).

$$\max \sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{x_i} \geq 1\ \forall \mathrm{cluster} \tag{4}$$

iv. Data transmission constraint: for a CH to relay data, its energy after transmission must above a minimum threshold as expressed in (5) where $\mathrm{e(P_i)}$ is the energy required for node i to transmit data.

$$\mathrm{E_{res,i}} - \mathrm{e(P_i)} \geq \mathrm{E_{th}},\ \forall \mathrm{i} \in \mathrm{N} \tag{5}$$

2.3. Knapsack algorithm for CH selection

The knapsack algorithm is applied to optimize CH selection in IoT-enabled WSNs. The process begins with initialization, where each node calculates its residual energy, distance to other nodes, and proximity to the BS. In the candidate CH selection phase, nodes with higher energy and closer proximity to the BS are shortlisted. The knapsack formulation evaluates each candidate based on weight (energy consumption and communication overhead) and value (residual energy contributing to network longevity).

Nodes with the highest value-to-weight ratio are selected as CHs, ensuring total energy consumption remains within the network's constraints. To optimize CH selection, the algorithm evaluates profit-to-weight ratio, similar to the 0/1 knapsack problem is described by (6). Where E_{res} represents the residual energy of a sensor node, and C_i denotes the associated cost function for selecting that node as a CH. This approach ensures energy-efficient CH selection, balancing energy consumption and prolonging network lifetime.

$$\text{maximize } \frac{E_{res,i}}{C_i} \tag{6}$$

2.4. Cluster formation

Once CHs are selected, sensor nodes form clusters based on proximity and signal strength. Each node calculates its distance to the nearest CH and joins the cluster that minimizes communication energy, ensuring efficient transmission. The association follows (7), where $\mathrm{d(i,j)}$ represents the Euclidean distance between node i and CH j, and $\mathrm{E_{th}}$ is the minimum energy threshold for communication.

$$\text{Cluster (i)} = \arg\min_{\mathrm{j}} \mathrm{d(i,j)} \text{ such that } E_{res,i} > \mathrm{E_{th}} \tag{7}$$

2.5. Data aggregation and transmission

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

2.6. Energy consumption model

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

- Transmission energy (E_{tx}): energy required to transmit data from node i to CH j is given (8).

$$E_{tx}(i,j) = E_{elec}\, d_{ij} \tag{8}$$

In this equation, E_{elec} represents the energy consumed per bit for operating the radio components, while d_{ij} denotes the spatial separation between node i and CH j.

- Reception energy (E_{rx}): energy consumed by the CH to receive data from a member node is expressed by (9).

$$E_{rx} = E_{elec} \tag{9}$$

- Aggregation energy ($\mathrm{E_{agg}}$): each CH consumes energy for data aggregation before transmitting to the BS which is expressed by (10) where E_{DA} is the data aggregation energy per bit, and n is the number of bits received.

$$\mathrm{E_{agg}} = \mathrm{E_{DA}} \,.\, \mathrm{n} \tag{10}$$

2.7. WSN knapsack algorithm for CH selection

The flowchart in Figure 3 represents the CH selection process for WSN based on the knapsack algorithm. It starts with the deployment and initialization of nodes and then moves to data collection and pre-processing. The process of selecting the CH is framed as a knapsack problem with energy constraints and communication efficiency. A fitness function determines the different CH configurations, and the selection algorithm is executed. If it does not yield the optimal CH configuration, it repeats; otherwise, clusters are formed, communication paths are laid down, and data is aggregated and transmitted to the BS. The network performance is evaluated, and if there is a change in network conditions, the selection process re-executes itself dynamically. If nothing changes, it terminates, ensuring that the WSN will operate energy-efficiently and adaptively under stable conditions.

The knapsack algorithm for node residual energy starts with the calculation of important parameters and thereafter forwards packets to nodes having more residual energy (E_{res}) can be see in Algorithm 1. In the case of a packet transmission, the algorithm determines if the node's residual energy (E_{res}) is greater than the energy required for transmission (e(Pi)). If so, then cluster residual strength (CRS) is calculated with the formula CRS = E_{res} - $e(P_i)$. If CRS exceeds the maximum threshold CRThmax, then the node will participate in the routing process; otherwise, it will be eliminated to save most of its energy and enhance the network lifetime.

Algorithm 1. Knapsack algorithm to compute node residual energy

Start
Calculating parameters node residual energy is used for high packet forwarding paths.
(E, E_{res}, $e(P_i)$)
Packet must in process == true
If ($E_{res} > e(P_i)$)
Compute (CRS = $E_{res} - e(P_i)$)
If (CRS > CRThmax)
Involve the Node in the routing process
Else Node cannot take part in the routing procedure.
End

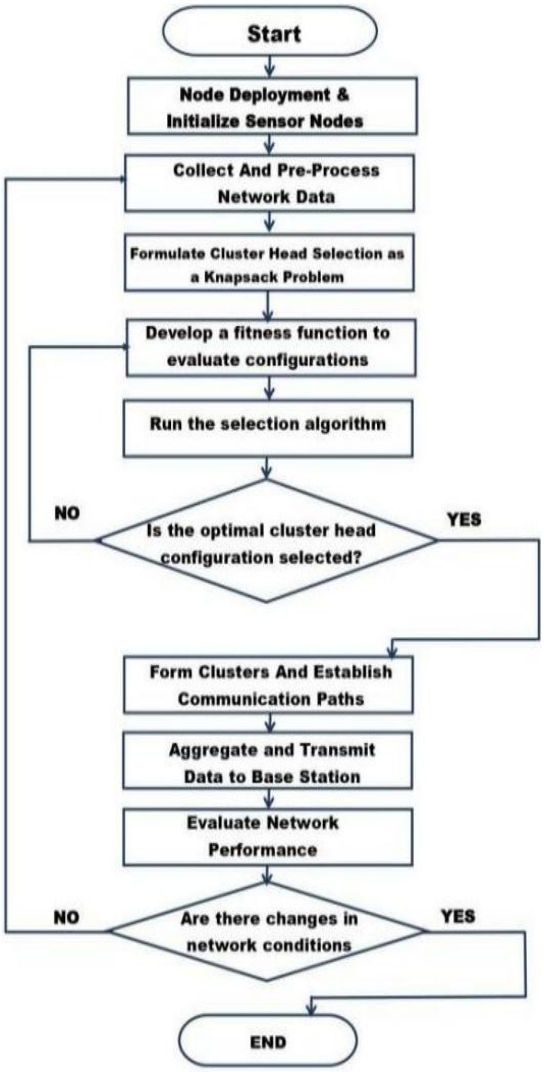

Figure 3. Workflow of the CH selection

3. SIMULATIONS RESULTS

Several simulations were executed to validate the effectiveness of the proposed knapsack algorithm for optimal CH selection in WSNs. Simulations were conducted using NS2.34/2.35, which indeed provided a platform for the implementation of the algorithm and also the visualization of results. The network topology was set in a two-dimensional 300 m×300 m area, which indeed represents an almost generic deployment scenario for WSNs. Within that area, 100 sensor nodes were randomly dispersed throughout the defined space. To mimic diversity in energy availability, each node was assigned a unique initial energy level sourced from a uniform distribution between 0.5 J and 1.5 J, as detailed in Table 1.

Table 1. Shows simulation specifications

S. No.	Parameter	Description
1	Nodes (numbers)	100
2	Channel type	Wireless
3	Received power	1 mw
4	Transmitted power	2 mw
5	Packet size	1,000 bits
6	Area (m)	300 m×300 m

In the IoT-based WSNs, the simulation results for the proposed EEKA demonstrate remarkable performance differences. The results indicate that EEKA optimizes the energy use evenly throughout the system by increasing network life 16%, data throughput by 17%, and delay by 14%. It displays disability to increase the reliability of real-time conditions by reducing total energy consumption by 12% and increasing network coverage by 20%. In terms of network life, efficiency of networks, and node survival probability, it is clear that the chosen CH based on Suitcase performs significantly better than PSO, GA, and GWO compared to other methods. Figure 4 shows how much longer the PSO-network life has been compared to EEKA-CH selection based on remaining energy, avoiding premature failure, and ensuring stability. Figure 5 shows the opposite effect on total consumed energy since it selects CHs far from member nodes instead of close ones. Figure 6 demonstrates that more nodes survive the simulation period, compared to PSO, GA, and GWO; there are approximately 30–35% more nodes alive at the 50% node death threshold. By avoiding early node depletion, this balanced consumption strategy keeps nodes active for a long time, guaranteeing connectivity as well. An overall comparison demonstrating EEKA's superiority across all evaluation criteria is shown in Figure 7. As further explained in Table 2, the combination of energetic-aware CH selection during cluster formation improves both communicational efficacy and energetic efficiency. providing a comparison of all performance metrics.

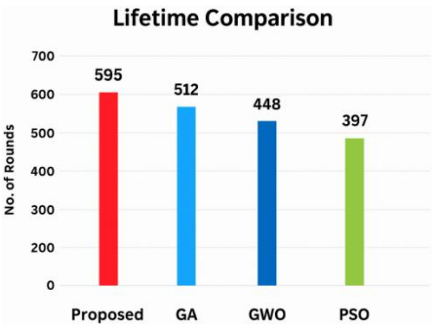

Figure 4. Lifetime comparison

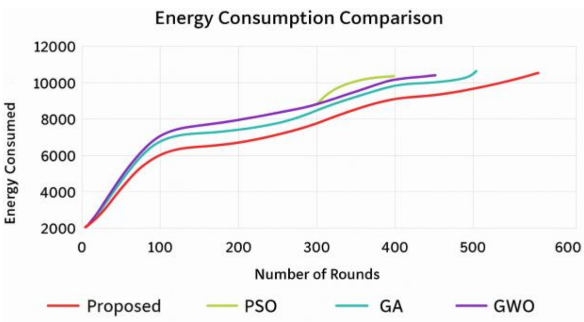

Figure 5. Energy consumption comparison

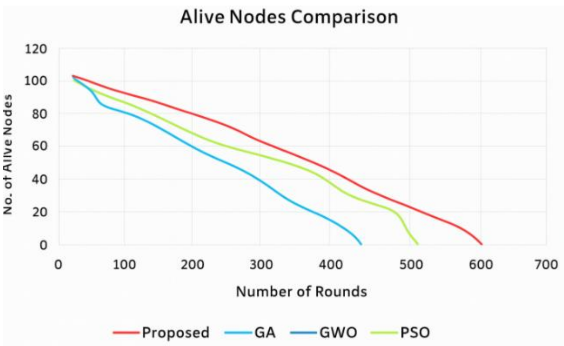

Figure 6. Alive node comparison

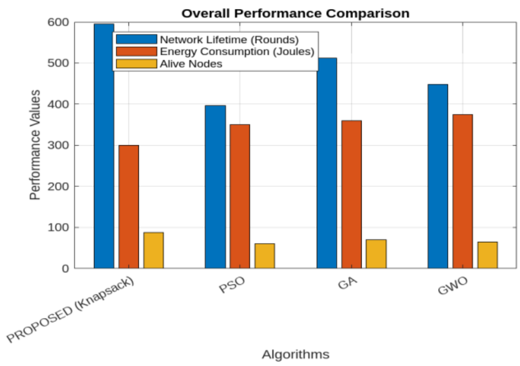

Figure 7. Shows overall parameter comparison

Table 2. Overall comparison of parameters

Parameters	PSO [22]	GA [7]	GWO [1]	Proposed (knapsack)
Network lifetime (s)	397	512	448	595
Energy consumption (J)	350	360	375	300
Number of alive nodes	60%	70%	65%	88%

4. CONCLUSION

The proposed knapsack algorithm-based approach improves CH selection in IoT-enabled WSNs by boosting energy efficiency, communication reliability, and overall network performance. Unlike heuristic methods, it dynamically assesses residual energy, communication costs, and IoT constraints, ensuring balanced energy use, lower re-clustering overhead, and efficient data transfer. Simulation results show a 16% increase in network lifetime, 17% higher throughput, a 14% decrease in latency, and a 20% boost in network coverage, confirming its effectiveness in real-time IoT applications like smart cities, industrial automation, and environmental monitoring. Future research should focus on validating these results with real-world Wi-Fi sensor networks, integrating machine learning for smarter CH selection, and exploring energy-efficient sensor hardware with energy-harvesting tech to enhance sustainability. Adding security features such as lightweight encryption and authentication will secure data transmission, while improving scalability will allow seamless operation in ultra-dense IoT networks. These improvements will make the knapsack algorithm-based CH selection smarter, more adaptable, and sustainable for long-term IoT-enabled WSN deployments.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Abdul Aleem		✓	✓		✓		✓		✓					
Rajesh Thumma										✓	✓	✓		

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY

The data used in this study is available upon request.

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