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# RECENT SURVEY ON OPTIMIZING 5G WIRELESS SENSOR NETWORKS WITH ADVANCED CLUSTERING AND DEEP BELIEF NETWORK ROUTING

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## ABSTRACT:
The Internet of Things (IoT) has driven advancements in constrained Wireless Sensor Networks (WSNs) to improve resource utilization and service delivery. Efficient communication and energy-efficient deployment are critical, especially in clustering and Cluster Head (CH) selection for data transmission. This framework introduces an energy-efficient Deep Belief Network (DBN)-based routing protocol to enhance packet delivery ratio (PDR). Initially, nodes are grouped into clusters using a reinforcement learning (RL) algorithm. The proposed DBN routing protocol is evaluated against existing algorithms, demonstrating superior performance in terms of network lifetime, energy consumption, and the number of alive nodes. This paper presents a comprehensive survey of advanced clustering and routing techniques, highlighting their impact on optimizing IoT-based constrained WSNs

## I. INTRODUCTION:
The evolution of wireless communication has progressed from 2G, enabling basic voice and data, to 3G [1], introducing multimedia capabilities with limited bandwidth. 4G brought significant bandwidth improvements, accommodating the rise in smartphone users globally. However, heavy traffic and quality of service (QoS) issues persisted. In response, 5G [2], deployed since 2019, offers up to 10 Gbps download speeds and broader bandwidth, utilizing small cells for enhanced data and video transmission capabilities.
The Internet of Things (IoT) leverages 5G communication to integrate into daily life, utilizing Wireless Sensor Networks (WSNs) [3] for monitoring environments due to their connectivity and mobility. Routing protocols in WSNs optimize energy efficiency and minimize delay[4], adapting to network density and traffic patterns. Machine learning algorithms [5], including deep learning such as Deep Belief Networks (DBN) [6], enhance routing and energy management, improving service quality through dynamic network analysis.

## II LITERATURE REVIEW
Numerous recent studies have focused on advancing routing protocols in both 5G wireless communication and Wireless Sensor Networks (WSNs), addressing critical challenges and optimizing network performance. For instance, research has introduced innovative approaches such as fuzzy logic-based clustering [7] and CLONALG-M [8], which enhance energy efficiency and improve load balancing in WSNs. These methods leverage adaptive immune system principles to achieve superior performance in network management.
Moreover, advancements in Neuro-Fuzzy routing techniques [9] and QoS-aware secure deep learning methods [10] have been pivotal. These approaches optimize cluster generation, improve parameters like delay and energy utilization, and ensure high-level security through innovative cryptographic techniques. Additionally, resilient routing algorithms [11] and blockchain-based frameworks [12] have been developed to enhance reliability, efficiency, and security in WSNs, integrating sophisticated technologies like deep learning and distributed ledger systems.
Furthermore, the integration of meta-heuristic approaches [13], hybrid optimization techniques [14,15], and multi-criteria decision-making methods [16] has significantly improved clustering, CH selection, and routing efficiency. These innovations aim to mitigate issues such as energy holes and optimize network lifetime through adaptive and scalable protocols. Dakshayini et al. (2013) developed an Improved Routing Algorithm to enhance energy efficiency in WSNs by minimizing communication distances and evenly distributing energy load among nodes.Li et al. (2013) proposed an Energy-Efficient Routing protocol using Particle Swarm Clustering and Inter-Cluster Routing in

WSNs, focusing on energy conservation, stable transmission, and load balancing.Rezvani et al. (2013) introduced an Iterative Algorithm to detect malicious data injections in WSNs, addressing collusion among compromised sensors for maintaining data integrity during event detection.

## III. PROBLEM IDENTIFICATION AND MOTIVATION

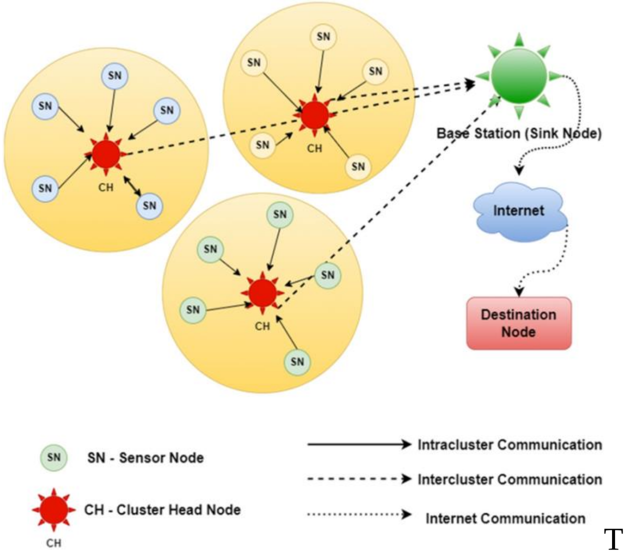
Developing efficient routing processes for Wireless Sensor Networks (WSN) assisted by IoT is crucial due to distinct characteristics like energy consumption and limited network lifetime. Unlike traditional wireless ad hoc networks, WSNs face unique challenges in routing data from Sensor Nodes (SNs) to Base Stations (BS). Three primary challenges include the absence of global addressing for numerous SN deployments, the need to consolidate data streams from multiple sources to specific sink nodes, and managing redundant data generated by multiple sensors in close proximity. These challenges result in increased energy consumption, bandwidth utilization, and operational issues such as delays and packet loss. To address these complexities, there is a growing interest in employing machine learning-based routing algorithms. These algorithms leverage past interactions to optimize decision-making for future data transmission actions, aiming to enhance overall network efficiency and performance in WSN-assisted IoT environments.

## IV. CHALLENGES IN 5G WIRELESS SENSOR NETWORKS

### A. NETWORK MODEL

The network model for Wireless Sensor Networks (WSN) in IoT optimizes communication efficiency through hierarchical clustering and machine learning-based routing. Key components include:

- Node Characteristics: Sensors categorized as advanced, intermediate, and normal based on network capabilities.
- Data Flow: Sensor data aggregated by Cluster Heads (CHs) and transmitted to a central Sink node for efficient data collection.
- Clustering: Reinforcement Learning (RL) algorithm clusters SNs to minimize energy consumption and extend network lifespan.
- CH Selection: Multi-Objective Modified Royal Food Optimization (MRFO) algorithm selects CHs based on delay, energy efficiency, traffic density, and distance.
- Routing Protocol: Deep Belief Neural Network (DBN) based protocol ensures energy-efficient data transmission by considering residual energy, distance, neighboring nodes, and link quality.
- Energy Model: Accounts for factors like free-space and multi-path fading to accurately estimate energy consumption during data transmission and reception.

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This approach aims to enhance WSN performance in data integrity, throughput, energy efficiency, and latency, crucial for sustainable IoT deployments in dynamic wireless environments.

### B. ENERGY MODEL

The energy model described for the radio energy dissipation in this work considers both free space and multi-path fading scenarios. Here are the equations and concepts involved:

$P_s = k * (P_{ec} + P_{frs} * dis^2)$; $dis < d_o$

$P_s = k * (P_{ec} + P_{mpf} * dis^4)$; $dis \geq d_o$ (1)

When the distance d between the transmitter and receiver exceeds a specified threshold, energy dissipation in free space is proportional to $d^2$.For distances beyond the threshold, energy dissipation due to multi-path fading is proportional to $d^4$. The energy consumption model $P_s$ during the transmission of the k-th bit packet is represented in (1).

$d_0 = \sqrt{P_{frs}/P_{mpf}}$ (2)

The requisite energy for transmitting the bit to the free-space via the multi-path fading channel is represented as $P_{frs}$and $P_{mpf}$ respectively. The threshold distance figured out using (2) is denoted as $d_0$.

The energy consumed while receiving a k bits of data packets is represented in (3),

$P_{rec} = k * P_{ec}$ (3)

During data aggregation, the energy consumed by CH is represented in (4),

$P_{agg} = P_{Eagg} * k * n$ (4)

where, n- number of messages, k - bits number in the data packet, and the total energy that is consumed while aggregating a single bit is represented as $P_{Eagg}$.

**C. CLUSTER GENERATION USING REINFORCEMENT LEARNING**

Reinforcement Learning (RL) in Wireless Sensor Networks (WSNs) involves agents (nodes) learning through actions and receiving rewards. Nodes cluster based on adjacent energy levels using RL algorithms, guided by Markov decision processes (MDP). Q-values assess route costs, aiding Cluster Head (CH) selection and optimizing energy consumption. RL continually updates policies to improve decision-making in the network environment.

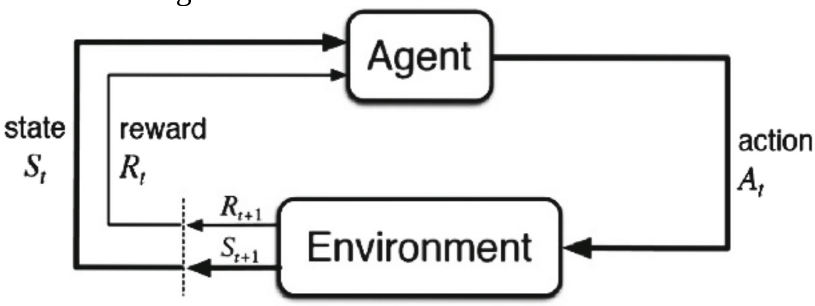


Fig 1: Reinforcement Learning (RL)

Algorithm 1 Algorithm for RL Based Cluster Generation

For each

State and action pair (S, α)

Initialize

Assign 0 to the table entry Q (S, α)

Do loop

Execute the selected action

Assign immediate reward R to the executed action.

Observe new state S and the entry Q (S, α) which is defined as follows,

$Q_{t+1}(S_t, \alpha_t) = (1 - \alpha)\, Q_t(S_t, \alpha_t) + \alpha\, [r^{t+1} + y \max Q_t(S_{t+1}, \alpha') - Q_t(S_t, \alpha_t)]$

$S = S'$

Select action

$\pi(S_i) = \arg\max \alpha Q(S, \alpha)$

Exploration $\frac{P(\alpha P\ i|S) = kQ(S,\alpha)}{\sum kQ(S,\alpha)}$

End loop

**D. DEEP BELIEF NETWORK BASED ROUTING**

Deep Belief Network (DBN), or probabilistic generative networks (PGN), is an efficient deep learning architecture with multiple layers. It includes hidden and visible neurons, where connections are adjusted by tunable weights—a critical feature. DBN incorporates layers like restricted Boltzmann machine (RBM) and multilayer perceptron (MLP), facilitating interaction between input and hidden layers for data processing.

Key components of DBN architecture:

- Sink: Destination node that gathers aggregated data.
- Action History: Communication of previously aggregated data before current aggregation.
- Future Node: Number of aggregated data sets (C) awaiting after current aggregation.
- Max-Distance Node: Node farthest from nearby nodes.

The initial hidden layer combines subsets of 4 neurons, each subset interconnected with respective input neurons. Moreover, DBN includes two hidden layers, each with 128 neurons, enhancing its capability in data representation and processing.

## V. EVALUATION METRICS

Evaluating the performance of 5G wireless sensor networks (WSNs) optimized with advanced clustering and deep belief network (DBN) routing requires a comprehensive set of metrics that provide a standardized means of assessment. Here's a detailed description of each evaluation metric for wireless sensor networks based on the provided text:

**1. Network Lifetime**

Network lifetime refers to the duration for which the network can operate before the first node exhausts its energy and can no longer participate in network activities. It is crucial for assessing the sustainability and reliability of the network over time.

**2. Throughput**

Throughput measures the rate at which packets are successfully received over time in the network.

**3. Number of Alive Nodes**

The number of alive nodes refers to the count of nodes in the network that have sufficient energy to actively participate in forwarding and receiving packets. It directly impacts the network's ability to function and its longevity.

**4. Energy Consumption**

Energy consumption evaluates the total energy utilized by Cluster Heads (CHs) and member nodes in the network.This metric helps in understanding the overall energy usage pattern of the network, which is crucial for managing and optimizing network resources.

## VI. CHALLENGES AND FUTURE RESERCH DIRECTION

Space and Time Complexity Analysis for Clustering

In this framework, a Reinforcement Learning (RL) algorithm is employed for clustering, offering superior time complexity when compared to traditional methods such as k-means and fuzzy c-means. The RL-based approach is optimized for clustering tasks, resulting in efficient performance even as the number of nodes increases. Moreover, it demonstrates improved space complexity due to its resource-efficient design.

Performance Enhancement: The RL-based clustering algorithm enhances overall performance by leveraging its learning strategy to optimize clustering outcomes effectively.

Space and Time Complexity Analysis for Routing

The analysis compares the time and space complexity of the proposed Dynamic Bayesian Network (DBN) routing approach with existing techniques like GIFSS-SSOGA, SSO, and GA algorithms. The DBN routing framework achieves superior efficiency in both time and space complexities.

Future enhancements could further improve the routing efficiency in the proposed framework by integrating these advancements in DBN-based routing. These enhancements would aim to optimize routing decisions and minimize computational overhead, potentially leading to enhanced overall network performance.

## VII CONCLUSION

These fundamental metrics are essential for evaluating wireless sensor network (WSN) performance: network lifetime, throughput, node capacity, and energy consumption management. Optimizing these metrics is critical for efficient WSN protocols and applications. Incorporating Reinforcement Learning (RL) and Deep Belief Network (DBN) approaches in clustering and routing significantly improves time and space complexity metrics while enhancing overall network performance. In conclusion, this paper highlights the integration of IoT with Wireless Sensor Networks (WSNs) through advanced clustering and DBN-based routing. The framework improves energy efficiency and enhances network performance, particularly in terms of packet delivery ratio and longevity. Future research should focus on further refining AI-driven routing algorithms and addressing remaining challenges like energy management and scalability to fully leverage the potential of IoT-enabled WSNs in diverse applications.

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