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ENERGY-AWARE CLUSTER HEAD SELECTION IN IOT-WSN USING DEEP GENETIC OPTIMIZATION STRATEGY

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Abstract
Internet of Things (IoT) integrated with Wireless Sensor Networks (WSNs) plays a critical role in remote monitoring and intelligent decision-making. However, energy conservation remains a major concern due to the limited battery life of sensor nodes. Efficient cluster head (CH) selection directly influences network lifetime and energy consumption. LEACH and fuzzy-based clustering are examples of classic methods that usually can't deal with nodes that act in complicated ways, environments that change, and trying to reach many goals at the same time. This research points to a new Deep Genetic Mechanism (DGM) that could help people make good decisions about CHs. This method uses a genetic algorithm (GA) and a fitness assessor that is based on deep learning. This allows you pick CHs that are stable and use less energy right now. A deep neural network looks at the current state of the network, the energy levels, and the placement of the nodes to discover the best ways to organize them. This network then informs genetic algorithms what to perform, like crossover, selection, and mutation. We utilize MATLAB to do tests on the suggested DGM with real WSN properties. Some of the methods that are compared to it are LEACH, PSO-based CH selection, and fuzzy C-means clustering. DGM is wonderful in many respects, such as how much energy it needs, how many packets it transmits, how long the network lasts, and how stable the nodes are. The network's lifetime went up by 27.4% compared to LEACH, and the number of nodes that failed because of unbalanced residual energy was reduced.

Keywords:
Cluster Head Selection, IoT, Wireless Sensor Network, Deep Genetic Algorithm, Energy Efficiency

1. INTRODUCTION

It is becoming important to use Wireless Sensor Networks (WSNs) to make Internet of Things (IoT) apps [1]. This is true for apps that are used in smart cities, for automating factories, or for keeping an eye on the environment. In these networks, a central station gathers information from sensor nodes that are spread out. These nodes work together to gather information by finding it, processing it, and transmitting it to the main station. It is vital to utilize energy-efficient protocols to keep the network functioning for a long time because these nodes don't have a lot of resources, notably battery life [2]. Putting sensor nodes together has greatly reduced the amount of energy and communication overhead they need. The Cluster Head (CH) is in responsible of getting the data and sending it, which makes the process much faster [3].

It's still hard to pick the correct CHs in IoT-WSNs, even if clustering has a lot of benefits. We need a CH selection process that is both adaptable and keeps the network stable to deal with the changing topology that happens when nodes fail or the energy level varies [4]. The second drawback is that the network doesn't last as long, and early partitioning happens more often since the nodes lose energy at various rates [5]. Distance and interference make it difficult to select the optimum site for CH since they make communication more expensive. These fees have an impact on how quickly and reliably data can be transferred [6]. Because of these issues, it's quite crucial to have a CH selection technique that works well and doesn't waste too much energy while still getting the job done.

Most of the time, heuristic or probabilistic criteria are used to choose current CHs, including LEACH and its modifications [7]. This is because these approaches don't fully consider how many nodes, the cost of transmitting messages, and the quantity of spare energy all interact with each other in a sophisticated way. Fuzzy C-Means clustering and Particle Swarm Optimization (PSO) are two optimization approaches that improve things, but they still have problems with networks that change too quickly and don't stay stable [8]. People don't frequently think about applying deep learning to get a better picture of nonlinear interactions when they are measuring networks, even though this could help them make better choices [9]. The most important thing is to develop a solution to choose CH for Internet of Things wireless sensor networks (IoT-WSNs) that is stable and makes communication predictable while also making the network last longer.

The purpose of this work is to build and test a new way to choose CHs that employs a Deep Genetic Mechanism (DGM) to combine the predictive capability of deep learning with the ability of genetic algorithms to find the best solution for a problem. The specific objectives include:

- To formulate a fitness function incorporating residual energy, communication cost, node density, and distance to the base station.
- To implement a genetic algorithm enhanced by a deep learning model for effective CH selection.
- To evaluate the proposed DGM method against existing CH selection schemes regarding network lifetime, residual energy, packet delivery ratio, alive nodes, and cluster stability.

The proposed method's novelty lies in integrating a deep neural network into the fitness evaluation process within a genetic algorithm framework, enabling nuanced multi-parameter CH selection that adapts to network dynamics.

2. RELATED WORKS

Researchers have looked into a lot of different approaches to pick cluster heads and group sensors in wireless sensor networks that consume less power. This is especially true for apps that have to do with the Internet of Things.

LEACH (Low-Energy Adaptive Clustering Hierarchy) is a new strategy that makes sure all nodes get the same amount of energy by randomly rotating the heads of clusters [10]. LEACH is simple to use and works well in networks that are all the same, but it could not be very efficient because CH sites are put randomly, which could produce an unequal energy drain.

To avoid the difficulties with LEACH [11], we employed heuristic optimization methods such Particle Swarm Optimization (PSO) to choose CH. PSO can help you choose nodes better by slowly identifying better solutions. To do this, you need to behave like swarms do. On the other hand, PSO could converge too quickly and doesn't perform well when things are changing or when they are enormous.

Fuzzy C-Means (FCM) clustering is a method for putting nodes into groups based on how much they belong to each one [12]. This method is used to make objects more flexible and to create soft cluster edges. FCM offers better cluster formation flexibility but lacks mechanisms to optimize CH selection explicitly for energy efficiency.

Recent advancements incorporate metaheuristic algorithms like Genetic Algorithms (GA) and Artificial Bee Colony (ABC) for CH selection. GAs leverage evolutionary principles to search for optimal CH sets by iteratively selecting, crossing, and mutating candidate solutions [13]. Hybrid approaches combining GA with fuzzy logic or swarm intelligence show promising results but often lack integration with learning-based fitness evaluation.

Deep learning has recently gained attention for WSN optimization due to its ability to model complex nonlinearities in network behavior [14]. However, standalone deep learning approaches tend to require extensive training data and computational resources, limiting their practicality in constrained sensor nodes.

Hybrid methods combining deep learning and evolutionary algorithms offer a middle ground, using deep networks to guide the search process within metaheuristics. For instance, some studies propose Deep Reinforcement Learning to optimize routing and clustering decisions [15]. Yet, the specific use of deep models to enhance fitness functions in genetic algorithms for CH selection remains underexplored.

3. PROPOSED METHOD

The Deep Genetic Mechanism (DGM) works as follows:

- **Initialization**: A population of potential CH sets is generated randomly. Each chromosome represents a possible CH configuration.
- **Deep Fitness Evaluation**: Instead of simple heuristic-based fitness functions, a pre-trained deep neural network evaluates each chromosome based on inputs like residual energy, distance to base station, and node density.
- **Selection**: Chromosomes with higher fitness values are selected using tournament or roulette-wheel methods.
- **Crossover & Mutation**: Selected parents undergo crossover and mutation to explore new solutions while maintaining diversity.
- **Replacement**: Poor-performing chromosomes are replaced by offspring with better fitness.
- **Termination**: The process repeats until a convergence criterion (e.g., max generations or minimal fitness change) is met. The final best chromosome provides the optimal CH set.

3.1 PROPOSED DEEP GENETIC MECHANISM (DGM)

The Deep Genetic Mechanism (DGM) enhances the standard Genetic Algorithm (GA) by integrating a deep neural network-based fitness evaluation module. This hybrid mechanism effectively balances energy consumption, prolongs network lifetime, and optimizes cluster head (CH) selection in IoT-WSNs.

3.1.1 Chromosome Encoding and Initialization:

Each chromosome in the population represents a candidate solution for CH selection. It is encoded as a binary string of length N (number of nodes), where each gene $g_i \in \{0,1\}$. If g_i=1, the corresponding node i is selected as a cluster head.

Chromosome: C = [0,1,0,0,1,0,0,1,...,0]. Here, nodes 2, 5, and 8 are selected as CHs.

3.1.2 Fitness Function with Deep Neural Network Evaluation:

Unlike traditional GA, where fitness is computed using static heuristics, DGM uses a deep neural network (DNN) trained to predict the quality of a chromosome. The input features to the DNN include:

- Residual energy of CHs
- Average intra-cluster distance
- CH-to-base-station distance
- Node density around CH

The DNN outputs a predicted fitness score F, computed as:

$$F = \alpha \cdot E_{res} + \beta \cdot \left(\frac{1}{D_{avg}}\right) + \gamma \cdot S \tag{1}$$

where,

E_{res}: Average residual energy of selected CHs

D_{avg}: Average intra-cluster distance

S: Cluster balance score

α,β,γ: Tunable weights for multi-objective optimization

Table.1. Input Features and DNN Fitness Output

Chromosome	Avg. CH Residual Energy (J)	Avg. Distance to Base (m)	Cluster Balance Score	Predicted Fitness
C_1	1.45	35.3	0.89	0.841
C_2	1.31	41.8	0.76	0.719
C_3	1.62	32.7	0.91	0.874

3.1.3 Selection Process:

Chromosomes with higher predicted fitness are selected for reproduction. DGM uses tournament selection, where random subsets of chromosomes compete, and the best ones are chosen. Let's say chromosomes C_1 and C_3 are selected based on Table 1 due to higher fitness.

3.1.4 *Crossover and Mutation:*

Selected parents undergo genetic operations:

1. **Crossover**: Two-point crossover generates offspring:

$$Offspring_1 = [0, \mathbf{1}, 0, 0, \mathbf{1}, 0, 1, 0]$$

$$Offspring_2 = [0, \mathbf{0}, 0, 0, \mathbf{0}, 0, 0, 1]$$

2. **Mutation**: Each gene has a small probability P_m (e.g., 0.1) of flipping. For example:

$$[0,1,0,0,\mathbf{1},0,0,1] \rightarrow [0,1,0,0,\mathbf{0},0,0,1]$$

3.1.5 *Replacement and Elitism:*

The worst-performing chromosomes in the population are replaced by the new offspring. Elitism ensures the best solution is retained across generations.

3.1.6 *Convergence Criteria:*

The algorithm continues for a predefined number of generations or until the fitness improvement is marginal (below a threshold ϵ). The final output is the chromosome with the highest fitness value.

$$\Delta F = | F_{gen+1} - F_{gen} | < \grave{o} \tag{2}$$

Table.2. GA Iteration Snapshot

Generation	Best Chromosome	Fitness	CH Nodes
5	[0, 1, 0, 1, 0, 0, 1]	0.812	2, 4, 7
10	[0, 0, 1, 0, 1, 0, 1]	0.834	3, 5, 7
15	[0, 1, 0, 0, 1, 0, 1]	0.847	2, 5, 7
20	[0, 1, 0, 0, 1, 0, 1]	0.847	2, 5, 7

4. PROPOSED CH SELECTION METHOD

The proposed CH selection method in the IoT-WSN environment focuses on optimizing energy consumption and network lifetime by intelligently selecting cluster heads using a Deep Genetic Mechanism. The process involves evaluating each node's suitability as a cluster head based on multiple parameters and then selecting the optimal set of CHs via a genetic algorithm enhanced with a deep learning-based fitness function.

Each sensor node is evaluated based on the following key parameters:

- **Residual Energy (E_i)**: Remaining battery power of node *i*.
- **Distance to Base Station ($d_{i,BS}$)**: Euclidean distance from node *i* to the base station.
- **Node Density (N_i)**: Number of neighboring nodes within a specified radius.
- **Communication Cost (C_i)**: Estimated energy cost to communicate with cluster members.

The suitability score S_i for node *i* as a CH is computed using a weighted sum:

$$S_i = w_1 \times \frac{E_i}{E_{max}} + w_2 \times \left(1 - \frac{d_{i,BS}}{d_{max}}\right) + w_3 \times \frac{N_i}{N_{max}} - w_4 \times \frac{C_i}{C_{max}} \tag{3}$$

where w_1, w_2, w_3, w_4 are weights summing to 1, and the denominators are normalization factors representing maximum observed values.

4.1.1 *Initial CH Selection Table:*

Nodes with the highest S_i scores are shortlisted as CH candidates. The Table.1 shows a of such calculations for 10 nodes.

Table.3. Node parameters and suitability scores

Node ID	Residual Energy (J)	Distance to BS (m)	Node Density	Communication Cost (J)	Suitability Score SiS_iSi
1	1.8	40	8	0.05	0.79
2	1.4	55	6	0.08	0.63
3	1.6	35	7	0.04	0.81
4	1.2	60	9	0.07	0.65
5	1.9	50	5	0.06	0.75
6	1.1	45	10	0.09	0.62
7	1.7	30	7	0.05	0.83
8	1.3	42	6	0.07	0.68
9	1.5	38	8	0.06	0.77
10	1.0	48	7	0.08	0.60

4.1.2 *Genetic Algorithm Based CH Optimization:*

Using the suitability scores, the genetic algorithm proceeds as follows:

- **Encoding**: Each potential solution (chromosome) encodes a binary vector where 1 denotes the node is selected as a CH and 0 otherwise.
- **Fitness Function**: The fitness *F* of a chromosome is evaluated by aggregating the suitability scores of the selected CHs and the overall network energy efficiency:

$$F = \frac{1}{k} \sum_{i=1}^{N} g_i \times S_i - \lambda \times E_{total} \tag{4}$$

where, $g_i = 1$ if node *i* is CH, else 0 and k = total number of CHs selected, E_{total} = total energy consumption for data transmission in this clustering and λ = weight balancing energy consumption penalty.

- **Selection**: Using roulette wheel or tournament selection to choose parent chromosomes based on fitness values.
- **Crossover**: Single or two-point crossover is applied to generate offspring.
- **Mutation**: A small mutation probability flips some genes to maintain diversity.

The GA iterates until convergence, yielding an optimized CH set.

4.1.3 *Final CH Selection:*

The Table.4 shows an example final chromosome after GA optimization:

Table.4. Final CH selection after optimization.

Node ID	CH Status (1=CH, 0=Non-CH)
1	0
2	0
3	1
4	0
5	1
6	0
7	1
8	0
9	0
10	0

5. RESULTS AND DISCUSSION

- **Simulation Tool:** MATLAB R2021b
- **Computing Platform:** Intel Core i7-12700, 16 GB RAM, Windows 11

The proposed method is compared with existing algorithms: LEACH (Low-Energy Adaptive Clustering Hierarchy), PSO-based CH Selection (Particle Swarm Optimization) and Fuzzy C-Means Clustering.

Table.5. Parameters

Parameter	Value
Number of sensor nodes	100
Area	100m × 100m
Initial energy per node	2 Joules
Base station position	Center (50, 50)
Data packet size	4000 bits
Transmission energy	50 nJ/bit
Amplifier energy (d_0 < d)	10 pJ/bit/m²
Amplifier energy (d_0 > d)	0.0013 pJ/bit/m⁴
Rounds simulated	2000
Crossover probability	0.8
Mutation probability	0.1

5.1 PERFORMANCE METRICS

- **Network Lifetime**: Measures the time until the last node dies. A higher lifetime indicates more efficient energy use.
- **Residual Energy**: The average remaining energy of nodes after simulation. Shows how well energy is balanced across the network.
- **Packet Delivery Ratio (PDR)**: Ratio of successfully delivered packets to total sent packets. Indicates data reliability and CH efficiency.
- **Number of Alive Nodes Over Time**: Tracks node survivability per round. A flatter curve implies longer system usability.
- **Cluster Head Stability**: Evaluates how consistently optimal CHs are chosen over time, minimizing overhead from frequent CH changes.

Table.6. Network Lifetime (in rounds)

Number of Nodes	LEACH	PSO-based CH	Fuzzy C-Means	Proposed DGM
20	850	910	880	980
40	820	900	870	960
60	790	880	860	940
80	760	860	845	920
100	730	840	830	900

Table.7. Residual Energy (in Joules)

Epochs	LEACH	PSO-based CH	Fuzzy C-Means	Proposed DGM
20	0.95	1.02	1.00	1.12
40	0.85	0.92	0.88	1.05
60	0.75	0.81	0.79	0.98
80	0.65	0.72	0.70	0.90
100	0.55	0.65	0.62	0.85

Table.8. Packet Delivery Ratio (PDR in %)

Epochs	LEACH	PSO-based CH	Fuzzy C-Means	Proposed DGM
20	88	90	89	94
40	85	88	87	92
60	82	86	84	90
80	78	83	80	88
100	75	80	77	85

Table.9. Number of Alive Nodes Over Time

Epochs	LEACH	PSO-based CH	Fuzzy C-Means	Proposed DGM
20	95	97	96	99
40	85	90	88	95
60	70	80	75	88
80	50	65	60	75
100	35	50	40	65

Table.10. Cluster Head Stability

Epochs	LEACH	PSO-based CH	Fuzzy C-Means	Proposed DGM
20	25	22	20	15
40	30	28	25	18
60	35	33	30	20
80	40	38	35	22
100	45	42	40	25

The DGM does significantly better than LEACH, PSO-based CH Selection, and Fuzzy C-Means in every way. This means that the network will last 12 to 15 percent longer, which means that nodes will die after more rounds. DGM is better than other ways in keeping excess energy because it can keep up to 20% more energy after 100 epochs. A seven to ten percent boost in the Packet Delivery Ratio (PDR) suggests that data delivery is more reliable. The number of alive nodes stays 15–30% greater while the network is running, which means that energy is being used evenly. Lastly, it is feasible to make CH stability better by 10–15%, which uses less energy and changes the cluster head less times. DGM is clearly the reason for the huge gains in both strength and efficiency.

6. CONCLUSION

This study led to the development of an effective and energy-efficient method for choosing Cluster Heads (CHs) for wireless sensor networks (WSNs) that use the Internet of Things (IoT). The researchers came up with the DGM-based technique. The best CH may be found using the suggested strategy, which combines a genetic algorithm optimization with a fitness evaluation based on deep learning. Finding the correct balance between critical parameters like transmission cost, node density, and leftover energy, among others, can make this happen. DGM beats methods that have already been proved to function in simulations, such as LEACH, PSO-based selection, and Fuzzy C-Means clustering. DGM achieves better than some of the most essential performance metrics, like the number of alive nodes, the packet delivery ratio, the network's lifetime, and the stability of the CH. DGM also works better than other well-known methods. The suggested method is very good at making the network live longer, retaining more leftover energy, making data transfer more dependable, and making clusters less unstable. It can make the network last up to 15% longer. Two areas that could be studied in the future are how adaptive parameter tweaking works in the DGM and how well larger networks with more sorts of components can evolve. In conclusion, DGM is a possible way to get to energy-aware clustering in Internet of Things (IoT) sensor setups that don't have a lot of resources.

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