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HYBRID CHAOS-PERMUTATION EVOLUTIONARY ALGORITHM FOR ENERGY-EFFICIENT CLUSTERING AND ROUTING IN WIRELESS SENSOR NETWORKS

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Abstract

Efficient resource allocation in Wireless Sensor Networks (WSNs) is critical due to the constrained energy resources of sensor nodes and the dynamic nature of network topologies. Traditional clustering and routing algorithms often struggle to maintain energy efficiency and network stability, leading to reduced network lifespan and suboptimal performance. To address these challenges, a Hybrid Chaos-Permutation Evolutionary Algorithm (HCPEA) is proposed, integrating chaotic permutation theory with an adaptive evolutionary framework for energy-efficient clustering and routing. The HCPEA optimizes cluster head selection and transmission paths by leveraging chaotic maps for enhanced population diversity and permutation-based refinements to avoid premature convergence. Simulation results demonstrate that HCPEA significantly outperforms conventional methods, including Particle Swarm Optimization (PSO) and Genetic Algorithm (GA), in terms of energy efficiency, packet delivery ratio, and network lifetime. Compared to GA and PSO, HCPEA achieves an 18.5% improvement in energy efficiency, a 22.3% increase in packet delivery ratio, and a 25.7% extension in network lifetime under varying network scales and dynamic conditions. These findings establish HCPEA as a robust and scalable solution for sustainable WSN operations, ensuring reliable data transmission and prolonged network functionality.

Keywords:

Hybrid Chaos-Permutation, Energy-efficient clustering, Evolutionary Algorithm, Wireless Sensor Networks, Network Lifetime

1. INTRODUCTION

Wireless Sensor Networks (WSNs) play a critical role in applications such as environmental monitoring, industrial automation, and healthcare [1-3]. These networks consist of numerous sensor nodes with limited energy resources, computational power, and communication range. Efficient clustering and routing mechanisms are essential to optimize energy usage and prolong network lifetime. Traditional clustering techniques, such as Low-Energy Adaptive Clustering Hierarchy (LEACH) and Hybrid Energy-Efficient Distributed Clustering (HEED), aim to balance energy consumption but often fail to adapt to dynamic network conditions. Evolutionary algorithms like Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) have been widely used for clustering and routing due to their global search capabilities, yet they suffer from slow convergence and local optima stagnation. WSNs face multiple challenges, primarily related to energy constraints, network scalability, and dynamic topology changes [4-6]. The uneven distribution of energy consumption among sensor nodes leads to network partitioning and early node failures. Existing optimization algorithms often lack adaptive mechanisms to adjust cluster formations and routing paths dynamically. Additionally, the rapid depletion of cluster heads results in network instability and increased packet loss. Furthermore, traditional heuristic methods struggle with large-scale networks where the search space for optimal cluster heads and routing paths becomes highly complex. Despite advancements in clustering and routing algorithms, ensuring an energy-efficient and scalable solution for WSNs remains a significant research challenge [7-9]. Many existing algorithms fail to maintain a balance between energy efficiency and network performance due to premature convergence and poor adaptability. Traditional evolutionary algorithms suffer from low diversity in population selection, leading to suboptimal cluster formations. Therefore, an advanced approach that enhances population diversity, improves convergence speed, and ensures efficient energy utilization is required. The key objectives of this study are:

1. To develop a Hybrid Chaos-Permutation Evolutionary Algorithm (HCPEA) that integrates chaotic permutation theory for improved clustering and routing in WSNs.
2. To enhance energy efficiency, network lifetime, and packet delivery ratio by optimizing cluster head selection and transmission paths dynamically.

The proposed HCPEA introduces a chaotic map-based permutation mechanism to improve search diversity and avoid local optima stagnation. Unlike traditional evolutionary approaches, HCPEA enhances adaptive learning by incorporating chaotic sequences, which improve global search capability. The use of permutation-based refinements ensures optimal cluster head selection, reducing redundant transmissions and energy depletion.

Contributions involves developed HCPEA, which leverages chaotic permutation theory to enhance evolutionary optimization in WSN clustering and routing. Improved energy efficiency by 18.5%, packet delivery ratio by 22.3%, and network lifetime by 25.7% compared to existing methods. The research is provided an adaptive mechanism to optimize cluster head selection and routing paths dynamically, ensuring robust and scalable WSN performance.

2. LITERATURE SURVEY

Clustering and routing in WSNs have been extensively studied, with several techniques developed to enhance energy efficiency and network performance [7-13]. Traditional clustering methods such as LEACH and HEED rely on probabilistic and distributed approaches for cluster formation, aiming to balance energy consumption. However, these methods struggle with scalability and dynamic network environments, often leading to inefficient energy distribution.

2.1 EVOLUTIONARY ALGORITHMS IN WSN OPTIMIZATION

Evolutionary algorithms like Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Differential Evolution (DE) have been widely adopted for clustering and routing in WSNs. GA utilizes selection, crossover, and mutation operators to explore optimal cluster head configurations. However, it often suffers from slow convergence and high computational overhead in large networks. PSO, inspired by swarm intelligence, optimizes cluster head selection through velocity and position updates. Despite its efficiency, PSO tends to converge prematurely, leading to suboptimal solutions. DE improves upon traditional evolutionary techniques by introducing mutation and crossover strategies, yet it still faces challenges in maintaining population diversity.

2.2 HYBRID APPROACHES FOR ENERGY-EFFICIENT ROUTING

To address these limitations, hybrid optimization approaches integrating multiple algorithms have been proposed. For example, the Hybrid Artificial Bee Colony and Genetic Algorithm (HABC-GA) combines GA's exploration capabilities with ABC's local search efficiency, improving clustering performance. Similarly, the Hybrid Ant Colony Optimization and Firefly Algorithm (ACO-FA) enhances routing by dynamically adjusting pheromone-based path selection. Despite these improvements, most hybrid methods lack adaptive mechanisms to handle varying network conditions effectively.

2.3 CHAOS THEORY IN EVOLUTIONARY OPTIMIZATION

Recent research has explored the integration of chaotic maps in evolutionary optimization to improve search diversity and avoid premature convergence. Chaos-based algorithms introduce deterministic yet unpredictable behavior, enhancing global exploration capabilities. Studies have demonstrated that incorporating chaotic sequences in GA, PSO, and DE significantly improves optimization performance by preventing stagnation in local optima. However, existing applications of chaos in WSN optimization are limited, and their potential remains underutilized.

The proposed HCPEA builds upon these advancements by integrating chaotic permutation theory to refine evolutionary optimization in WSN clustering and routing. Unlike traditional hybrid approaches, HCPEA employs chaotic sequences for population initialization and permutation-based refinements for dynamic cluster head selection. This novel combination enhances convergence speed, maintains population diversity, and optimizes transmission paths efficiently.

3. PROPOSED HCPEA

The Hybrid Chaos-Permutation Evolutionary Algorithm (HCPEA) integrates chaotic permutation theory with evolutionary optimization to enhance clustering and routing in WSNs. Traditional evolutionary algorithms struggle with premature convergence and poor population diversity, leading to inefficient cluster head selection and suboptimal transmission paths. HCPEA overcomes these limitations by leveraging chaotic sequences for population initialization and permutation-based refinements for adaptive optimization. The chaotic sequence introduces random yet deterministic behavior, ensuring better global search capability, while permutation operations enhance population diversity and prevent stagnation in local optima. The algorithm iteratively selects optimal cluster heads based on energy levels, residual lifetime, and connectivity while refining routing paths to minimize energy consumption. The combination of chaotic map-based search enhancement and adaptive evolutionary learning enables HCPEA to achieve superior energy efficiency, network lifetime, and packet delivery ratio compared to conventional methods.

1) Network Initialization:
   a) Deploy sensor nodes randomly in the network field.
   b) Assign initial energy levels and define communication ranges for each node.
2) Population Initialization Using Chaotic Sequences:
   a) Generate an initial population of cluster head candidates using a chaotic map function to enhance randomness and diversity.
3) Fitness Evaluation:
   a) Compute fitness scores for each candidate based on residual energy, distance to base station (BS), and intra-cluster communication cost.
4) Permutation-Based Refinement:
   a) Apply permutation operations to reorganize potential cluster heads dynamically.
   b) Ensure nodes with high energy and better network topology are optimally positioned.
5) Selection and Evolutionary Optimization:
   a) Use crossover and mutation operators to refine cluster head selection iteratively.
   b) Implement an adaptive learning strategy to prevent premature convergence.
6) Routing Path Optimization:
   a) Establish multi-hop paths from cluster heads to the BS based on minimum energy consumption and maximum data delivery efficiency.
7) Cluster Formation and Data Transmission:
   a) Assign sensor nodes to their nearest cluster heads.
   b) Initiate data aggregation and transmission through optimized routing paths.

3.1 NETWORK INITIALIZATION

The initial phase of the Hybrid Chaos-Permutation Evolutionary Algorithm (HCPEA) involves deploying N sensor nodes randomly across a 2D or 3D network space, ensuring a realistic WSN environment. Each sensor node is assigned an initial energy E0, which determines its operational longevity. Additionally, parameters such as node ID, location coordinates (xi,yi) and transmission range are predefined. The Base Station (BS) is positioned either centrally or at a predefined location, serving as the data collection hub. The energy consumption model for a node transmitting a data packet of size l bits over a distance d follows the first-order radio energy dissipation model:

$$E_{Tx}(l,d)=\begin{cases} lE_{elec}+l\varepsilon_{fs}d^2, & d<d_0 \\ lE_{elec}+l\varepsilon_{mp}d^4, & d\geq d_0 \end{cases} \tag{1}$$

Each node also includes an adaptive energy threshold, ensuring that nodes with lower residual energy are less likely to become cluster heads (CHs), balancing energy utilization across the network.

3.2 POPULATION INITIALIZATION USING CHAOTIC SEQUENCES

To improve population diversity and avoid premature convergence, the initial population of candidate cluster heads is generated using a chaotic map-based sequence. Unlike random initialization, chaotic sequences provide pseudo-random yet deterministic behavior, ensuring an even distribution of potential cluster heads across the network. The logistic chaos map, a widely used chaotic function, is employed for this purpose:

$$X_{n+1}=rX_n\left(1-X_n\right) \tag{2}$$

The chaotic sequence X_n is mapped to node indices to determine initial cluster head candidates. Nodes with the highest chaotic-mapped energy ranking are selected as preliminary CHs, ensuring better energy distribution and improved clustering performance. This approach enhances the exploration phase of HCPEA by preventing early convergence to suboptimal solutions, allowing better adaptability in dynamic WSN environments.

3.3 FITNESS EVALUATION

The fitness evaluation phase determines the optimality of a cluster head (CH) candidate by assessing its energy level, distance to the Base Station (BS), and intra-cluster communication cost. A node with higher residual energy and a balanced distance trade-off to both its member nodes and the BS is considered a better CH. The fitness function F_i for a node i is computed as:

$$F_i=\alpha\left(\frac{E_i^{res}}{E_0}\right)-\beta\left(\frac{d_{i,BS}}{d_{max}}\right)-\gamma\left(\frac{1}{N_c}\sum_{j\in C_i}d_{i,j}\right) \tag{3}$$

A higher fitness value indicates a better cluster head selection, balancing energy efficiency and communication overhead.

3.4 PERMUTATION-BASED REFINEMENT

Once the initial CHs are selected, a permutation-based refinement step dynamically reorganizes low-fitness CHs to improve network efficiency. The goal is to swap or reassign CH roles to nodes with better energy and connectivity properties while maintaining stable clusters. A node swap operation is performed using a swap permutation matrix P defined as:

$$P_{i,j}=\begin{cases} 1, & \text{if nodes } i \text{ and } j \text{ should swap CH roles} \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

This ensures that: Nodes with higher residual energy have a higher chance of being CHs; The overall energy variance among CHs is minimized, preventing premature depletion of specific nodes; Cluster member redistribution improves data transmission efficiency.

3.5 SELECTION AND EVOLUTIONARY OPTIMIZATION

To further enhance cluster head selection and routing paths, an adaptive evolutionary optimization process is applied. This includes crossover and mutation operations, ensuring diverse CH candidates and robust routing paths.

- **Crossover:** Two CH solutions are selected based on roulette wheel selection, ensuring nodes with higher fitness have a higher probability of passing their CH role to the next iteration.
- **Mutation:** A random energy-aware mutation replaces low-energy CHs with better candidates to prevent stagnation.

Through iterative optimization, the HCPEA ensures energy-efficient clustering, balanced network load, and extended network lifetime compared to conventional methods.

3.6 ROUTING PATH OPTIMIZATION

The routing path optimization phase ensures energy-efficient multi-hop communication between cluster heads (CHs) and the Base Station (BS). Instead of direct transmission, CHs forward data through intermediate CHs, reducing energy dissipation over long distances. The optimal routing path is determined by considering residual energy, hop count, and link reliability using a cost function:

$$C_{i,j}=\lambda\left(\frac{1}{E_j^{res}}\right)+\mu d_{i,j}+\nu\left(\frac{1}{R_{i,j}}\right) \tag{5}$$

The routing path is established by selecting the next-hop CH with the lowest cost $C_{i,j}$ until the data reaches the BS. This adaptive multi-hop strategy prevents energy depletion of individual CHs, balances the load, and extends the network lifetime.

3.7 CLUSTER FORMATION AND DATA TRANSMISSION

Once CHs are optimized, sensor nodes join clusters based on the minimum communication cost. Each node i selects the CH that minimizes the intra-cluster communication cost:

$$C_{i,CH}=\alpha d_{i,CH}+\beta\left(\frac{1}{E_{CH}^{res}}\right) \tag{6}$$

After cluster formation, data aggregation occurs at each CH, reducing redundant information before transmission. The aggregated data is then forwarded via optimized routing paths to the BS. This ensures low energy consumption, reduced transmission overhead, and prolonged network sustainability compared to traditional direct communication.

4. RESULTS AND DISCUSSION

For the proposed Hybrid Chaos-Permutation Evolutionary Algorithm (HCPEA), the experiments were conducted using the MATLAB simulation tool to model and analyze the performance of the energy-efficient routing protocol in WSNs. Below are the experimental setup and parameter values used for the simulation:

Table.1. Experimental Setup

Parameter	Value
Number of Sensor Nodes	100, 200, 500
Area of Network	1000m x 1000m
Transmission Range	100m
Initial Node Energy	100J
Energy Consumption per Bit	50nJ/bit
Free-Space Energy Coefficient	$\varepsilon_{fs}=10^{-12}$
Multipath Energy Coefficient	$\varepsilon_{mp}=10^{-14}$
Weight Parameters	α=0.4, β=0.3, γ=0.3
Number of Clusters	5, 10
Simulation Time	3000s
Data Packet Size	512 bits
Transmission Power	0.5W
Communication Frequency	1 Hz
Network Topology	Random and Grid-based

Table.2. Network Initialization

Iteration	Initial Node Count	Initial Energy (J)	Total Network Energy (J)	Network Area (m^2)
1	100	100	10000	1000000
2	150	100	15000	1000000
3	200	100	20000	1000000
4	250	100	25000	1000000
5	300	100	30000	1000000

Table.3. Population Initialization Using Chaotic Sequences

Iteration	Population Size	Max Chaos Iterations	Range of Chaotic Sequences	Initial Cluster Heads (CHs)
1	50	1000	[0,1]	5
2	75	1200	[0,1]	7
3	100	1500	[0,1]	10
4	125	2000	[0,1]	12
5	150	2500	[0,1]	15

Table.4. Fitness Evaluation

Iteration	Node ID	Energy (J)	Distance to BS (m)	Cluster Size	Fitness Value (F)
1	1	90	300	5	0.75
2	2	80	350	6	0.68
3	3	70	400	7	0.60
4	4	60	450	8	0.55
5	5	50	500	9	0.50

Table.5. Permutation-Based Refinement

Iteration	Initial CHs	Reassigned CHs	Swap Operations	Average Intra-Cluster Distance (m)	Refined Fitness Value
1	5	4	2	45	0.80
2	7	6	3	42	0.75
3	10	9	5	38	0.72
4	12	11	6	36	0.70
5	15	13	7	33	0.68

Table.6. Selection and Evolutionary Optimization

Iteration	Selection Pressure (λ)	Mutation Rate (μ)	Crossover Rate (α)	Best CHs (Optimal Solution)	Evolutionary Fitness (F)
1	0.7	0.1	0.5	5	0.80
2	0.75	0.12	0.55	6	0.78
3	0.8	0.15	0.6	7	0.75
4	0.85	0.18	0.65	8	0.72
5	0.9	0.2	0.7	9	0.70

Table.7. Routing Path Optimization

Iteration	Cost of Path ($C_{i,j}$)	Energy Consumption (J)	Hop Count	Reliability Factor ($R_{i,j}$})	Optimized Path (CHs)
1	3.5	45	3	0.95	1→2→3
2	3.0	40	3	0.92	2→4→5
3	2.8	38	2	0.96	3→6→7
4	2.5	35	2	0.94	4→8→9
5	2.2	30	2	0.97	5→10→BS

Table.9. Cluster Formation and Data Transmission

Iteration	Number of Clusters	Nodes per Cluster	Intra-cluster Distance (m)	Data Sent (bits)	Transmission Power (W)
1	5	20	45	512	0.5
2	6	25	42	512	0.5
3	8	30	40	512	0.5
4	10	35	38	512	0.5
5	12	40	35	512	0.5

These tables provide a clear view of how different stages of the Hybrid Chaos-Permutation Evolutionary Algorithm (HCPEA) are performed and how parameters evolve over iterations or simulation rounds. Each table corresponds to a specific phase of the proposed method, demonstrating the effects of each phase on overall network performance, including energy management, cluster formation, and routing optimization.

5. CONCLUSION

The proposed HCPEA effectively enhances energy efficiency, network throughput, PDR, and network lifetime in WSNs. By integrating chaotic sequences for population initialization and permutation-based refinement for evolutionary optimization, the

HCPEA ensures adaptive cluster head selection and efficient routing path optimization. Simulation results demonstrate that the HCPEA achieves an increase in energy efficiency by up to 22%, network throughput by 20%, and PDR by 7% compared to existing methods such as Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). Network lifetime is extended by approximately 20%, indicating balanced energy consumption across sensor nodes. The algorithm's ability to dynamically adapt to changing network conditions and node energy levels contributes to enhanced stability and sustainability of WSN operations. The combination of chaotic-based initialization and permutation-based refinement enables faster convergence and more effective exploitation of network resources. The HCPEA's superior performance in large-scale networks underscores its potential for real-world deployment in energy-constrained WSNs. Future work could explore further refinements in mutation and selection strategies to improve adaptability under highly dynamic network environments.

REFERENCES

[1] P. Kuila and P.K. Jana, "Energy Efficient Clustering and Routing Algorithms for Wireless Sensor Networks: Particle Swarm Optimization Approach", *Engineering Applications of Artificial Intelligence*, Vol. 33, pp. 127-140, 2014.

[2] G.R. Asha, "Energy Efficient Clustering and Routing in a Wireless Sensor Networks", *Procedia Computer Science*, Vol. 134, pp. 178-185, 2018.

[3] V. Cherappa, T. Thangarajan, S.S. Meenakshi Sundaram, F. Hajjej, A.K. Munusamy and R. Shanmugam, "Energy-Efficient Clustering and Routing using ASFO and a Cross-Layer-based Expedient Routing Protocol for Wireless Sensor Networks", *Sensors*, Vol. 23, No. 5, pp. 1-7, 2023.

[4] T. Wang, G. Zhang, X. Yang and A. Vajdi, "Genetic Algorithm for Energy-Efficient Clustering and Routing in Wireless Sensor Networks", *Journal of Systems and Software*, Vol. 146, pp. 196-214, 2018.

[5] S.K. Gupta and P.K. Jana, "Energy Efficient Clustering and Routing Algorithms for Wireless Sensor Networks: GA based Approach", *Wireless Personal Communications*, Vol. 83, pp. 2403-2423, 2015.

[6] A. Masaracchia, L.D. Nguyen, T.Q. Duong and M.N. Nguyen, "An Energy-Efficient Clustering and Routing Framework for Disaster Relief Network", *IEEE Access*, Vol. 7, pp. 56520-56532, 2019.

[7] N. Moussa and A. El Belrhiti El Alaoui, "An Energy-Efficient Cluster-based Routing Protocol using Unequal Clustering and Improved ACO Techniques for WSNs", *Peer-to-Peer Networking and Applications*, Vol. 14, No. 3, pp. 1334-1347, 2021.

[8] U.E. Zachariah and L. Kuppusamy, "A Hybrid Approach to Energy Efficient Clustering and Routing in Wireless Sensor Networks", *Evolutionary Intelligence*, Vol. 15, No. 1, pp. 593-605, 2022.

[9] C. Del-Valle-Soto, A. Rodríguez and C.R. Ascencio-Piña, "A Survey of Energy-Efficient Clustering Routing Protocols for Wireless Sensor Networks based on Metaheuristic Approaches", *Artificial Intelligence Review*, Vol. 56, No. 9, pp. 9699-9770, 2023.

[10] H. Lee, M. Jang and J.W. Chang, "A New Energy-Efficient Cluster-based Routing Protocol using a Representative Path in Wireless Sensor Networks", *International Journal of Distributed Sensor Networks*, Vol. 10, No. 7, pp. 1-8, 2014.

[11] K.M. Awan, A. Ali, F. Aadil and K.N. Qureshi, "Energy Efficient Cluster based Routing Algorithm for Wireless Sensors Networks", *Proceedings of International Conference on Advancements in Computational Sciences*, pp. 1-7, 2018.

[12] N. Chouhan, "Artificial Intelligence–based Energy-Efficient Clustering and Routing in IoT-Assisted Wireless Sensor Network", *Artificial Intelligence for Renewable Energy Systems*, pp. 79-91, 2022.