Energy-Aware Clustering in IoT-WSNs via Particle Swarm Optimization

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***Abstract*—Energy-efficient clustering is critical for extending the operational lifetime of IoT-enabled wireless sensor networks (WSNs). This paper proposes a particle swarm optimization (PSO)–based clustering protocol that utilizes a double-exponential adaptive inertia weight mechanism to dynamically balance global exploration and local exploitation, thereby preventing premature convergence and improving cluster head (CH) selection accuracy. The proposed technique dynamically determines the optimal number of clusters based on residual node energy and forms uniformly sized clusters by assigning high-energy, well-positioned nodes as CHs. Simulation results across diverse network topologies show that the proposed method outperforms benchmark protocols, including LEACH, LEACH-FL, and LEACH-FC, achieving notable improvements in node survivability, network longevity, and energy efficiency. The results confirm that the proposed algorithm effectively reduces communication distances, balances transmission load, and significantly prolongs the lifetime of IoT-based WSNs.**

I. Introduction

PSO is a population-based optimization technique inspired by the collective behavior of biological swarms, such as the coordinated movements of bird flocks and fish schools [1]. Metaheuristic algorithms are characterized by their low implementation complexity, simple mathematical structure, and flexibility, making them highly suitable for solving challenging optimization problems. These methods have been effectively applied to a broad spectrum of research domains, including both linear and nonlinear optimization, multi-objective problem solving, and other complex computational tasks. In particular, metaheuristic approaches have demonstrated strong performance in applications such as rapid UAV deployment, neural network training, solving nonlinear optimization problems, network security, node localization in wireless sensor networks (WSNs), and robotic path planning and tracking [2].

In the PSO algorithm, a swarm is composed of simple agents, referred to as particles, each of which represents a candidate solution in the search space. The search process is guided by iterative updates of two fundamental attributes: the velocity and the position of each particle expressed as

$$v_i^k = \omega_k v_i^{k-1} + c_1 R_1 (P_{best,i} - x_i^{k-1}) + c_2 R_2 (G_{best} - x_i^{k-1}), \quad (1)$$

$$x_i^k = x_i^{k-1} + v_i^k, \quad (2)$$

Where, v_i^k denotes the updated velocity of the particle, while v_i^{k-1} corresponds to its velocity at the previous iteration.

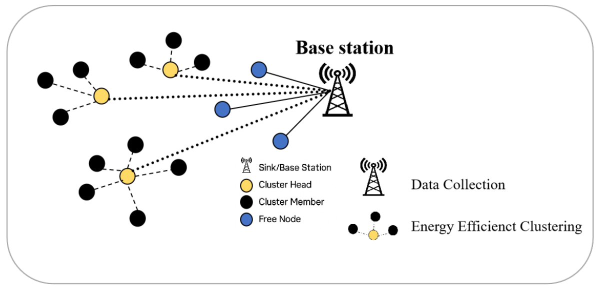

Fig. 1. IoT-based WSN structure.

The term $P_{i,\text{best}}$ represents the best position attained by an individual particle, whereas G_{best} refers to the best solution identified by the entire swarm. The acceleration parameters C_1 and C_2 regulate the relative influence of the particle's personal experience and the collective experience of the swarm, guiding its motion toward the global optimum [3]. Specifically, C_1 characterizes the particle's cognitive tendency to explore and exploit its own best-known position, while C_2 captures its social tendency to follow the globally best solution. These acceleration coefficients can be adaptively tuned over time through a time-varying acceleration strategy, as defined below.

$$C_1 = (c_{1i} - c_{1f}) \times \frac{i}{iter_{\max}} + c_i, \quad (3)$$

$$C_2 = (c_{2f} - c_{2i}) \times \frac{i}{iter_{\max}} + c_{2i}, \quad (4)$$

The range of acceleration coefficients is within [0.5, 2.5]. The value of C_1 changing from 2.5 to 0.5 and value of C_2 changes from 0.5 to 2.5. The basic idea of Iot-based WSN structure is shown in Fig. 1.

II. Contribution

This paper introduces an adaptive inertia weight mechanism integrated into the PSO algorithm for energy-aware clustering in IoT-enabled wireless sensor networks, where the inertia weight is continuously adjusted according to the convergence behavior of the clustering process. The adaptive inertia factor, denoted by ω, controls the trade-off between global exploration and local exploitation during cluster head selection. Its value is automatically updated at each iteration based on the current optimization stage. In the early iterations, higher population diversity is promoted to explore a wide range of

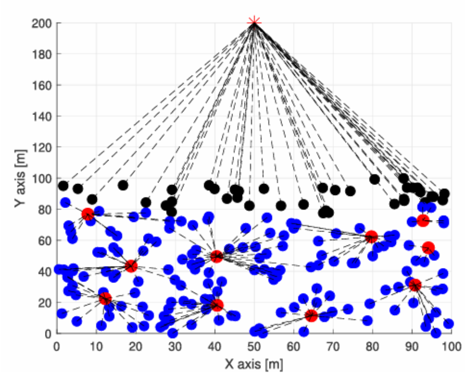

Fig. 2. Cluster Head selection.

feasible clustering configurations, while in the later stages, the algorithm focuses on refining promising solutions to achieve accurate and stable cluster head assignments as shown in Fig. 2 . To meet these conflicting objectives, a self-adaptive inertia weight strategy is employed. In the proposed Adaptive-PSO framework, the inertia weight is updated as follows:

$$w^{(k)} = w_{\min} + (w_{\max} - w_{\min}) \cdot e^{-\frac{k}{(k_{\max}/10)}} \tag{5}$$

The inertia weight updating rule represents an exponentially decreasing adaptive inertia mechanism in the PSO algorithm. At the beginning of the optimization process, the inertia weight remains close to $w_{\max}$, which encourages global exploration and allows particles to search a wider solution space. As the number of iterations increases, the inertia weight gradually decreases toward $w_{\min}$, strengthening local exploitation and enabling fine adjustment of promising solutions. This strategy effectively balances exploration and exploitation, reduces the risk of premature convergence, and improves the stability and accuracy of the optimization process, making it particularly suitable for energy-aware clustering in IoT-based wireless sensor networks. The fitness function is therefore created to represent the goal of energy efficent IoT-enabled wireless sensor networks is expressed as

$$\begin{aligned} \mathrm{F}_t &= a \cdot \sum_{i=1}^{n} E_t(N_i) \\ &+ (1-a) \cdot n \cdot \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} \left(R_t(N_i) - \frac{1}{n} \sum_{j=1}^{n} R_t(N_j) \right)^2}, \end{aligned} \tag{6}$$

III. Experimental results

Fig. 3 comparative performance analysis of LEACH, LEACH-FL, LEACH-FC, and the proposed algorithm was conducted using standard network lifetime metrics. In the medium-density 160-node IoT-based WSN scenario with a fixed cluster head (CH) ratio of 10%, the proposed algorithm consistently outperformed LEACH, LEACH-FL, and LEACH-FC in terms of network lifetime metrics. The first node death

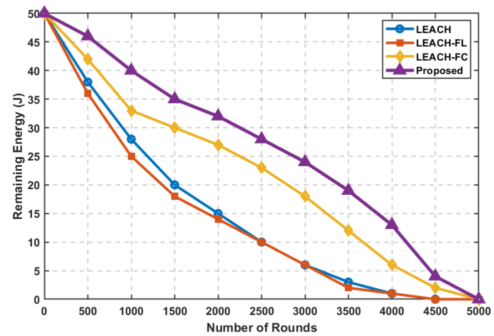

Fig. 3. Remaining network energy vs. no. rounds

(FND) was observed at 1759 rounds, demonstrating significant improvements of 41.3% over LEACH, 36.5% over LEACH-FL, and 22.7% over KM-PSO, which indicates superior early-stage energy balancing and load distribution. The half node death (HND) occurred at 4119 rounds, reflecting an 17.9% improvement over LEACH, highlighting more efficient energy conservation during the mid-life phase of network operation. Furthermore, the last node death (LND) was achieved at 4500 rounds, representing a 26.5% enhancement over LEACH and a 2.4% improvement over LEACH-FC, confirming the proposed method's ability to maintain stable and prolonged network operation. These results demonstrate the strong scalability and energy efficiency of the proposed clustering strategy in medium-density IoT-based wireless sensor networks.

IV. Conclusion

This paper proposes a PSO-based clustering algorithm incorporating a exponential adaptive inertia weight to enhance energy efficiency and prolong network lifetime in IoT-enabled wireless sensor networks. The algorithm utilizes residual node energy and location information to dynamically optimize the number of clusters and intelligently select high-energy nodes as cluster heads, ensuring balanced energy consumption. The performance of the proposed method is evaluated in a single network scenario and compared with LEACH, LEACH-FL, and LEACH-FC. Simulation results demonstrate that the proposed approach achieves superior energy efficiency and longer network lifetime than the benchmark protocols. Although the results are promising, the current study assumes ideal network conditions; future work will investigate performance under dynamic and real-world IoT environments.

V. Acknowledgement

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