CEPSO: A Novel Clustering Algorithm for Enhancing the Lifetime and Energy Efficiency of Wireless Sensor Networks in Power Grids

2024 9th International Conference on Automation, Control and Robotics Engineering (CACRE) | 979-8-3503-5030-2/24/$31.00 ©2024 IEEE | DOI: 10.1109/CACRE62362.2024.10634869

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***Abstract*—Facing numerous challenges in traditional Power Grid Wireless Sensor Networks (PGWSNs), including inaccurate node clustering, low energy efficiency, and shortened network lifetime, this study proposes an innovative energy-efficient clustering algorithm—an improved Particle Swarm Optimization algorithm (CEPSO). The algorithm employs a unique elite strategy by constructing a multi-level elite pool to retain outstanding individuals generated during iterations, thereby accelerating the iterative process. To address the complexity and diversity of the power grid environment, the algorithm incorporates Cubic chaotic mapping to enhance performance and adaptability to complex environments. By comparing and analyzing with traditional clustering methods such as LEACH, SEP and standard PSO, the CEPSO algorithm underwent extensive simulation tests on key metrics such as network delay, energy consumption reduction, and network lifetime extension. The research results indicate that the CEPSO algorithm significantly outperforms the compared algorithms in all performance metrics, providing an efficient solution for extending the lifetime of PGWSNs.**

Keywords—Grid Wireless Sensor Networks, Improved Particle Swarm Optimization, Energy-efficient clustering

I. INTRODUCTION

In recent years, Wireless Sensor Networks (WSNs) technology has rapidly developed. WSNs consist of various types of sensor nodes, forming extensive monitoring networks to accurately collect field information. In power grid environments, these networks enable wireless communication via single-hop or multi-hop routing and play a crucial role in extreme environment monitoring[1, 2].

Despite their easy deployment, these micro sensors are limited by battery energy, making it challenging to extend WSNs' lifespan. Researchers have proposed various clustering-based protocols to improve energy efficiency and extend lifespan. Recently, computational intelligence techniques such as neural networks, reinforcement learning, and swarm intelligence have been widely applied to solve WSN design issues, including cluster head selection, clustering optimization, network security, data aggregation, and time synchronization.

Given the close correlation and interdependence of nodes, traditional predefined clustering rules are no longer suitable. Additionally, the dynamic nature of power grid environments requires algorithms to adapt to energy consumption, network density changes, and environmental fluctuations. Swarm intelligence algorithms, especially PSO, have gained attention for their excellent global search capabilities and adaptive solutions. ACO algorithms, which mimic ant foraging behavior, effectively balance energy consumption and extend network lifespan[3].

Clustering methods in PGWSNs are based on bio-inspired algorithms, which are capable of providing optimal clustering solutions within a limited time. Arjunan, S and Sujatha, P[4]. developed an algorithm called Fuzzy Logic and ACO Hybrid Protocol, which combines fuzzy logic and ACO techniques for CH selection and routing optimization. Although the algorithm demonstrates significant energy efficiency and network lifetime extension, it still has certain limitations in handling complex real-time data transmission requirements. Considering factors such as node residual energy, distance to the base station, and node density, the algorithm can achieve energy balance and effective CH selection under uneven network conditions[5].

Maheshwari, P; Sharma, AK and Verma, K[6]. developed an energy-efficient Cluster Head selection and routing optimization algorithm called Butterfly Optimization Algorithm and Ant Colony Optimization (BOA-ACO). This algorithm utilizes the Butterfly Optimization Algorithm for CH selection and employs the Ant Colony Optimization algorithm to determine the optimal routing path from the CH to the base station. Although the BOA-ACO algorithm shows significant energy efficiency and network lifetime improvement, it still has limitations in handling complex real-time data transmission requirements. Therefore, by considering factors such as node residual energy, physical distance, and node density, this algorithm effectively achieves energy balance and CH selection under uneven network conditions.

Kotary, DK and Nanda, SJ[7]. proposed a distributed robust data clustering algorithm for WSNs based on Diffusion Moth Flame Optimization (DMFO). This algorithm employs a diffusion strategy, collaborating by sharing the best moth positions and corresponding fitness values to ensure globally optimal cluster partitions at each sensor node. Although DMFO demonstrates superior cluster quality and computational efficiency, its complexity significantly increases when handling larger datasets and a higher number of sensor nodes, as the size of sensor data and the number of nodes increase, the runtime of DMFO also increases, indicating that further optimization is needed for its application in dynamic WSNs.

Over time, various optimization strategies have increasingly been used to enhance the global search performance of bio-inspired algorithms. Chaotic strategies can effectively improve the global search ability of algorithms. For example, Sivakumar, D; Devi, SS and Nalini, T[8]. developed an energy-aware clustering protocol (EACP-CGTOA) using the Chaotic Gorilla Troops Optimization Algorithm (CGTOA) for WSNs. This algorithm improves the diversity of solutions and algorithm performance by using circular chaotic mapping to replace population initialization. The EACP-CGTOA model constructs a fitness function based on neighbor distance, distance to the base station, and energy ratio, achieving good optimization results.

Elite strategies are an effective means of enhancing the convergence speed of bio-inspired algorithms. Gong, YP; Li, CQ and Fang, XS[9]. integrated elite strategies into the cloning process of snake optimization, effectively improving the algorithm's convergence speed. Similarly, Xie, JP et al[10]. combined elite strategies with the Seagull Optimization Algorithm, applying it to solve complex problems in intelligent poultry farming. Nevertheless, these strategies have not been able to retain all historically excellent individuals, leading to the loss of some superior solutions during iterations.

Overall, Despite the extensive exploration of various clustering methods in existing literature, many of these approaches often overlook key factors such as node residual energy, intra-cluster distance, and the distance to the base station, which are vital for the clustering performance of PGWSNs. To bridge this research gap, this paper introduces a new clustering model specifically designed for PGWSNs and proposes an innovative bio-inspired clustering method that integrates chaotic mapping with a multi-elite pool strategy to achieve the optimal clustering scheme. Moreover, by developing new chaotic mapping and elite strategies, this study aims to enhance the algorithm's search efficiency and solution quality, thereby speeding up its convergence. Through these strategies, the study seeks to optimize energy efficiency in PGWSNs and significantly prolong the lifespan of WSNs in power grid systems, offering an efficient and practical solution for future PGWSNs deployments.

II. System Model

In PGWSNs, the integrated energy model plays a crucial role in calculating energy consumption. The energy used for a link includes both the transmission and reception of data. PGWSNs nodes are equipped with data aggregation functions, which notably reduce the data volume that cluster heads (CHs) need to send. Consequently, this decreases the energy consumption associated with data transmission in PGWSNs. The overall energy consumption model can be summarized as follows:

$$E_m = E_{\mathrm{sd}}(m,d) + E_{\mathrm{rv}}(m,d) + E_{\mathrm{rh}}(m,d) \tag{1}$$

In this model, the energy consumption is determined by the distance between the transmitter and receiver, utilizing either the free space channel or the multipath fading channel. If the distance is below the threshold d_0 the free space (is) model is employed; if the distance is equal to or exceeds d_0 the multipath (smp) model is applied. Let E_{elec}. present the energy required by the electronic circuits, and $\varepsilon_{\mathrm{smp}}$, epresent the energy required by the amplifier in the free space and multipath models, respectively. The energy required to transmit m bits of data over a distance d can be expressed as follows:

$$\begin{aligned} E_{\mathrm{sd}}(m,d) &= E_{\mathrm{sd-dec}}(m) + E_{\mathrm{sd-amp}}(m,d) \\ &= \begin{cases} mE_{\mathrm{elec}} + m\varepsilon_{\mathrm{is}} d^2, d < d_0 \\ mE_{\mathrm{elec}} + m\varepsilon_{\mathrm{smp}} d^4, d..d_0 \end{cases} \end{aligned} \tag{2}$$

The energy consumption for a data receiving node to receive m bits of data is given by:

$$E_{\mathrm{rv}}(m,d) = mE_{\mathrm{elec}} + m\varepsilon_{\mathrm{is}} d^2 \tag{3}$$

The amount of energy required to perform data fusion on m bits of data is:

$$E_{da}(m,d) = mE_{elec} \tag{4}$$

E_{elec} depends on several factors, such as digital coding, modulation, filtering, and signal spreading. The amplifier energy $\varepsilon_{\mathrm{is}} d^2 / \varepsilon_{\mathrm{smp}} d^4$. depends on the distance between the transmitter and receiver, as well as the acceptable bit error rate. The distance threshold d_0 is defined as $\sqrt{\varepsilon_{fs} / \varepsilon_{mp}}$, When the distance is less than the threshold d_0 , the free space propagation model is used to calculate energy consumption; when the distance is equal to or greater than d_0 , the multipath attenuation model is applied. In both cases, the energy consumption for transmitting 1 bit of data is denoted as E_e. The energy loss coefficient for free space propagation is ε_{fs} ,and for multipath propagation, it is ε_{mp}.

During data communication, non-cluster head nodes, after sensing data from the collection point, send this data to the cluster head node they belong to. Typically, the distance from these non-cluster head nodes to the cluster head is relatively short, so data transmission follows the free space propagation model. Based on this model, the energy consumption required when a non-cluster member node transmits k bits of information can be calculated using the following formula:

$$E_{non-ch}(i) = kE_e + k\varepsilon_{fs} D^2_{Clusters}(i,j) \tag{5}$$

Here, $D^2_{Clusters}(i,j)$ represents the distance between non-cluster node i and its corresponding cluster head j. The cluster head node first receives data from its cluster members, then integrates this data with the information collected from the monitoring terminal. The aggregated data is subsequently transmitted to the base station. This section assumes that in each data transmission cycle, the cluster head node processes and transmits k bits of data to the sink node, and the energy consumption during this process can be calculated using a specific formula.

$$E_{ch} = \left(\frac{alive}{\text{cluster}} - 1\right) kE_e + \frac{alive}{\text{cluster}} kE_{CE} + kE_e + \begin{cases} k\varepsilon_{fs} d^2_{toBS} \\ k\varepsilon_{mp} d^4_{toBS} \end{cases} \tag{6}$$

The energy consumption mainly consists of three parts: receiving energy, processing energy, and transmission energy. Here, alive represents the number of monitoring terminal nodes that are still operational, cluster denotes the total number of clusters, and E_{CE} refers to the energy consumed by the cluster head node during data processing and reception.

The grid wireless sensor system network model in this paper is shown in Fig.1:

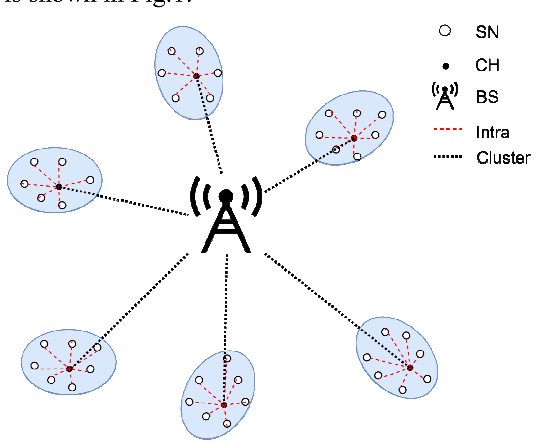

fig 1. PGWSNs networks model

III. CEPSO FOR PGWSNS

In the model presented in this paper, special consideration is given to large-scale power grid monitoring environments where the base station is positioned centrally within the region. Despite the base station's central location, significant distances exist between monitoring points and the base station, resulting in substantial energy loss. Consequently, the energy consumed by nodes transmitting information to the base station is proportional to their relative distance to the base station, whether the data is transmitted directly (single-hop) or via intermediate nodes (multi-hop). As a result, nodes closer to the base station deplete their energy more quickly than those further away.

To optimize the energy usage efficiency of nodes within the network, this paper proposes an algorithm that divides the monitoring area and introduces varying competition radii to form clusters of different sizes. This approach addresses the "hot spot" phenomenon caused by uneven energy consumption, thereby extending the network's service life and ensuring the continuous stability of power grid monitoring, leading to more efficient energy management and network operation.

Currently, many heuristic clustering algorithms used for PGWSNs face issues of local optima and uneven energy distribution. To address these problems, this study proposes a cluster routing strategy based on the CEPSO algorithm. The CEPSO algorithm draws inspiration from the foraging behavior of birds, demonstrating excellent global search capabilities and the ability to converge quickly and stably. In this algorithm, each particle represents a potential solution, and by simulating the iterative update process of the population, the optimal solution is gradually discovered. This algorithm not only features rapid convergence but is also relatively simple to implement, making it suitable for practical deployment.

The following sections will provide a detailed introduction to the key aspects of the CEPSO algorithm, including the objective function, the encoding scheme and initial setup of particles, position updates, and the overall algorithmic workflow.

A. *Encoding Scheme And Initialization*

In the context of PGWSNs, the initial steps for implementing CEPSO for clustered routing strategies involve selecting the encoding method for the algorithm. While both binary and integer encoding techniques are widely used, binary encoding appears to be more suitable for nodes in PGWSNs. In this case, the size of the particle swarm remains constant at p, and each particle represents a specific clustered routing configuration throughout the process, with its length equivalent to the total number of wireless sensor nodes in the PGWSNs.

$$G = \begin{bmatrix} g_{1,1} & g_{1,2} & g_{1,3} & \cdots & g_{1,s-1} & g_{1,s} \\ g_{2,1} & g_{2,2} & g_{2,3} & \cdots & g_{2,s-1} & g_{2,s} \\ \cdots & \cdots & \cdots & g_{i,j} & \cdots & \cdots \\ g_{p-1,1} & g_{p-1,2} & g_{p-1,3} & \cdots & g_{p-1,s-1} & g_{p-1,s} \\ g_{p,1} & g_{p,2} & g_{p,3} & \cdots & g_{p,s-1} & g_{p,s} \end{bmatrix} \begin{cases} g_{i,j} \in \{0,1\} \\ i \in [1,p] \\ j \in [1,s] \end{cases} \tag{7}$$

Assuming the total number of sensors in the PGWSNs is S, the particle swarm G can be defined as shown in (7). In this setting, the length of all particles within the swarm is S, with values limited to either 0 or 1. Here, 1 indicates that the node is a Cluster Head (CH), while 0 indicates that the node is a Cluster Member (CM). In each round, the ratio of nodes designated as CHs and CMs will not exceed the predefined proportion BCH. The number of cluster head nodes is given by: $CH_{num} = S*BCH$.

B. Update The State

In the context of PGWSNs, for the CEPSO algorithm, the position characteristics of particles are crucial as they represent potential solutions. Simultaneously, velocity directly influences the update of positions, making the precise adjustment of position and velocity update strategies particularly important. Based on (8) and (9), the state of each sample is updated as follows:

$$v_{i,t+1} = \eta * v_{i,t} + c_1 * r_1 * \left(p_{i,t} - s_{i,t}\right) + c_2 * r_2 * \left(p_{g,t} - s_{i,t}\right) \quad (8)$$

$$s_{i,t+1} = s_{i,t} + v_{i,t+1} + \xi * x_{i,t+1} \quad (9)$$

Here, $v_{i,t}$ and $v_{i,t+1}$ represent the velocity of the particle at generation t and t+1, respectively. Similarly, $s_{i,t}$ and $s_{i,t+1}$ denote the position of the particle at generation t and t+1, respectively. $p_{i,t}$ and $p_{g,t}$ represent the particle's historical best position and the global best position from generation t, respectively. η indicates the inertia weight of the particle. $x_{i,t+1}$ is the chaotic factor at generation t+1, and ξ is the influence coefficient of this chaotic factor. c_1 and c_2 re learning parameters, generally set to 2. r_1 and r_2 re two independent random numbers ranging between 0 and 1.This method not only emphasizes the importance of optimizing routing selection in PGWSNs but also considers the dynamic adjustment of particle positions and velocities to adapt to the exploration of the solution space, thereby further optimizing the energy-efficient clustering routing problem in Grid Wireless Sensor Networks.

C. CEPSO Algorithm Flow

The execution process of the CEPSO algorithm is as follows. Meanwhile, Algorithm 1 represents the pseudocode for CEPSO cluster head selection optimization in PGWSNs.

Step 1. Initialize the CEPSO parameters for clustering in PGWSNs, including the maximum number of iterations, the number of sensors, the population size, and the chaotic factor. Randomly generate the initial population using (7) and deploy the PGWSNs.

Step 2. Calculate the fitness values of the population according to the fitness function, and record the historical best values of the particles and the global best value of the population.

Step 3. Calculate and update the velocity of the particles using (8).

Step 4. Update the positions of the particles using a chaotic optimization strategy based on (9).

Step 5. Apply the elite strategy to update the contents of the elite pool and include them in the next iteration.

Step 6. Constrain the velocity and position of the population within specified ranges.

Step 7. Check if the number of iterations has reached the set value. If so, the algorithm terminates and outputs the optimal solution. Otherwise, continue to execute Step 2.

Algorithm 1 Procedure for CEPSO in PGWSNs

Require: Population size NUM; Maximum number of iterations MAX_iter; Sensor nodes S; Cluster head nodes CH_num; Field size n×m;

Ensure: The optimal solution;

1. Initialize CEPSO parameters for PGWSNs;
2. Randomly initialize the velocities and positions of k particles;
3. Initialize parameters of the Cubic chaotic strategy;
4. While i < MAX_iter do
5. Calculate the fitness of the population;
6. Record the best particle and the global best fitness;
7. Update the velocities of the population;
8. Execute the Cubic chaotic mapping strategy;
9. Update the multi-elite pool;
10. Constrain the velocities and positions of the population;
11. End while;
12. Return the optimal solution.

IV. EXPERIMENT AND ANALYSIS

In this section, to validate the effectiveness of the CEPSO protocol in PGWSNs, this study compares it with the LEACH, SEP, and standard PSO clustering algorithms. Each clustering algorithm operates in rounds. The practicality and efficiency of the CEPSO algorithm are evaluated through systematic monitoring, recording, and analysis of node energy consumption and clustering performance.

The experiments were conducted using MATLAB 2020b software on a computer equipped with an Intel (R) Core (TM) i5-13500H CPU and 16GB of memory, running Windows 10. This setup ensures the stability and reliability of the experiments, allowing for an accurate reflection of the performance characteristics and advantages of the CEPSO algorithm in practical applications.

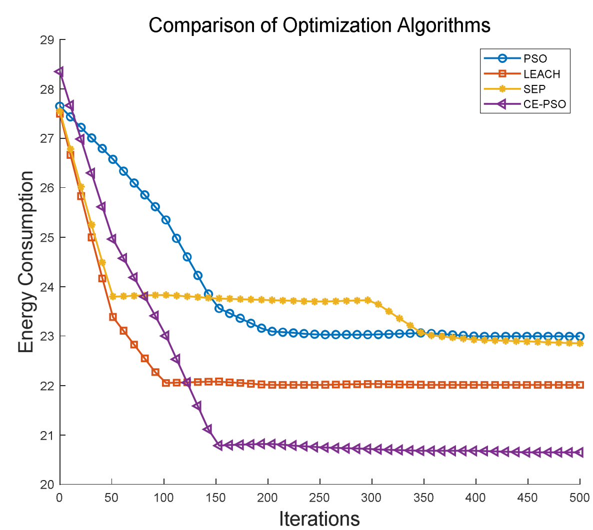

fig 2. Comparison of optimization algorithms

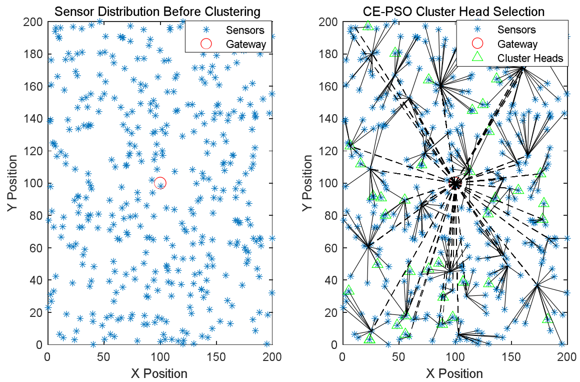

fig 3. PGWSNs clustering diagram

In the experimental section of this paper, the performance of four optimization algorithms in Power Grid Wireless Sensor Networks (PGWSNs) is compared: PSO, LEACH, SEP, and the proposed CEPSO. The results in Fig.2 indicate that in the initial iteration process, the cost function values of PSO and LEACH rapidly decline, but they tend to stabilize after approximately 100 iterations, with relatively high final cost function values. The performance of the SEP algorithm is slightly better than that of the PSO and LEACH algorithms but still inferior to the CEPSO algorithm. CEPSO exhibits the fastest convergence rate and the lowest final cost function value, demonstrating significant advantages.

Fig.3 shows the distribution of sensor nodes before and after clustering. The left panel displays the random distribution of nodes, while the right panel shows the distribution after cluster head selection using the CEPSO algorithm. Cluster head nodes are marked with green triangles and are connected to the central gateway node, forming an efficient data transmission path. Through the optimization of the CEPSO algorithm, the sensor network achieves effective cluster head selection, significantly improving energy efficiency and network lifespan.

V. CONCLUSION

Therefore, an innovative clustering algorithm, CEPSO, has been proposed and applied to enhance the energy efficiency and optimize the lifespan of PGWSNs. In this study, we first introduced a new algorithm that combines a unique elite strategy with chaotic mapping to overcome the limitations of traditional clustering methods. Numerical simulations were conducted using CEPSO, LEACH, SEP, and standard PSO, and the results were compared to validate the effectiveness of CEPSO. The results show that CEPSO demonstrates significant advantages in key performance indicators, such as reducing energy consumption and extending network lifetime, compared to LEACH, SEP, and standard PSO. This algorithm is stronger and more efficient than existing heuristic methods, capable of avoiding local optima while searching for better solutions.

ACKNOWLEDGMENT

This paper was funded by the project of National Key Research and Development Program of the Corps: Research and application demonstration of information technology based on source-grid-load-storage and multi-energy complementarity, grant number: 2023AB021; National Key Research and Development Program of the Corps: Key Technology Research and Application for High Penetration New Energy Grid Dispatch, grant number: 2023AB010; National Key Research and Development Program of the Corps: Research and application demonstration of key technologies for panoramic monitoring, perception and intelligent control of large-scale distributed photovoltaic bases, grant number: S2023AA5383; National Key Research and Development Program of the Corps: R&D and demonstration of the intelligent supervision platform for the inspection and testing institutions of the Corps based on big data and artificial intelligence, grant number: S2024AB048; Young scientific and technological innovation talents: key technological innovation and application of integrated energy intelligent management and control and precise low-carbon dispatching, grant number: 2023TSYCCx0120; Research on the application of "Internet +" customer service based on the comprehensive energy big data of the XPCC, grant number: KXO0760202.

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