

SEP Routing Protocol Based on Hybrid-Strategy Improved Whale Optimization Algorithm

Mingshi Luo, Han Xu

School of Computer Science, Xi'an University of Petroleum, Xi'an 710065, China

Abstract: Aiming at the problems of unreasonable cluster head election, uneven energy consumption and short network life cycle in wireless sensor networks with Stable Election Protocol (SEP) cluster head election is unreasonable, uneven energy consumption and short network life cycle in wireless sensor networks, a SEP routing protocol based on hybrid strategy whale optimization (HWO-SEP) is proposed. Optimize the population initialization and enhance the population diversity by Tent chaotic mapping with adversarial learning strategy. Design nonlinear convergence factor with dynamic spiral parameters, combined with adaptive inertia weighting model to balance the ability of global exploration and local exploitation. Construct a multi-objective fitness function to optimize the cluster head election process by comprehensively considering the cluster head residual energy, intra-cluster communication cost and distance to the base station. Simulation experiments show that the improved protocol network stability is improved by 47.75%, 31.38%, and 16.35% compared with LEACH, SEP, and WOA-SEP, respectively

Keywords: Whale Optimization Algorithm; SEP Routing Protocol; Energy Balance; Wireless Sensor Network; Network Lifecycle

1. Introduction

Wireless Sensor Network (WSN) has shown great application potential in the fields of environmental monitoring, smart agriculture, and industrial IoT [1] due to its low-cost, self-organized miniature sensor nodes to achieve real-time sensing and data interaction of the physical world. However, with the complexity of application scenarios, traditional wireless sensor networks have been exposed to problems such as uneven energy consumption [4] and short lifespan [5], and heterogeneous networks are often used in practical applications to reduce costs, but such hybrid deployments pose higher challenges to the design of routing protocols, and efficiently utilizing the energy of nodes and effectively prolonging the network lifespan have become the focus of current research[6].

Currently, routing protocols are mainly divided into planar routing protocols and hierarchical routing protocols [7]. LEACH [8] is one of the earliest cluster routing protocols, which achieves load balancing by randomly rotating cluster heads, but its assumption that the network is isomorphic and ignores the residual energy of the nodes leads to irrational cluster head election in heterogeneous scenarios; the SEP protocol, based on the improvement of LEACH, achieves energy balancing by differentiating cluster head election. The SEP protocol is improved based on LEACH protocol and achieves energy equalization by differentiating the cluster head election probability [9]. The core idea is to give high energy nodes a greater probability to become cluster heads and more data forwarding work, thus reducing the energy consumption rate of low energy nodes and prolonging the stable operation time of the network. However, the distribution of nodes in the network is not taken into account. Zhao X[10] et al. improve the fitness function of the Gray Wolf optimization algorithm, comprehensively consider the residual energy and the distance to the base station, to achieve the optimal election of the cluster head, but do not take into account the cost of intra-cluster communication. Han H[11]

et al. on the problems of high energy consumption of nodes in the traditional routing protocols, low efficiency of data transmission, and the high mortality rate of the nodes, propose a method based on the improvement of the ant colony algorithm for route optimization. By introducing an energy consumption heuristic factor, the probability of ants choosing a path is dynamically adjusted to avoid premature node energy depletion, the range of pheromone concentration is limited to avoid premature convergence of the algorithm, and the global search capability is enhanced by the global and local update strategies, node mortality rate is reduced, and the network life cycle is extended. Aiming at the problem of short network lifetime due to uneven energy consumption in wireless sensor networks, Hongyuan Gao [12] et al. proposed a cluster routing protocol based on quantum coyote optimization algorithm, which reduces the network load and energy consumption by means of dynamic centralized cluster formation, localized cluster head rotation and relay transmission strategies. The above optimizations for routing protocols extend the network life cycle to some extent, but still have shortcomings.

Combining the whale optimization algorithm, a SEP routing protocol based on mixed-strategy whale optimization is proposed, which improves the population initialization through Tent chaotic mapping and adversarial learning, designs the nonlinear convergence factor and the dynamic spiral factor, improves the global search and local exploitation ability of the whale optimization algorithm, sets the multidimensional fitness function, and comprehensively considers the residual energy of the cluster head, the cost of intra-cluster communication, the cost of communication between the cluster head and the terminal nodes, and applies to the SEP protocol cluster head election process to equalize the energy consumption of nodes. communication cost of cluster head and terminal nodes, which is applied to the cluster head election process of SEP protocol to equalize the energy consumption of nodes and prolong the network stabilization period.

2. Wireless Sensor Network System Model

2.1. Network Models

In this paper, the network model is set as follows: (1) sensor nodes have the same initial energy and all nodes are functionally equivalent; (2) the network consists of a base station and multiple sensor nodes, which are non-uniformly and randomly distributed within the area $M \times M$ and their locations do not change any more; (3) based on the strength of the received signals, the sensor nodes can compute the communication distance between them and the transmitter. (4) The sensor nodes are able to adjust the transmit power based on the sending distance; (5) The base station has abundant energy reserves and excellent processing performance.

2.2. Energy Consumption Models

The consumption of energy in the network has a direct impact on its life cycle, the new algorithm selects a first order wireless communication model, the transmission energy consumption required by a node to send n bit data to another node at a distance d is shown in equation (1):

$$E_{Tx}(n, d) = n \cdot E_{elec} + n \cdot \alpha_{amp}(d) \quad (1)$$

$$\alpha_{amp}(d) = \begin{cases} \varepsilon_{fs} \cdot d^2, & d < d_0 \\ \varepsilon_{amp} \cdot d^4, & d > d_0 \end{cases} \quad (2)$$

Where, E_{elec} is the energy required to transmit 1bit of data by the transmitter or receiver circuit, ε_{fs} is the amplification factor of the free space fading model; ε_{amp} is the amplification factor of the multipath channel fading model; and d_0 is the distance threshold, according to which the energy consumption model will be selected during the network operation. d_0 is defined as shown in equation (3):

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{amp}}} \quad (3)$$

The energy consumed by the sensor node to receive n bit data is shown in equation (4):

$$E_{Rx} = n \cdot E_{elec} \quad (4)$$

3. Improved Whale Optimization Algorithm Based on Mixed Strategies

Whale Optimization Algorithm (WOA) is an intelligent optimization algorithm proposed by Mirjalili et al [13] in 2016. Compared with traditional algorithms, WOA shows stronger global search ability and stability in solving high-dimensional nonlinear problems, and becomes one of the important methods in the field of intelligent optimization.

WOA establishes the mapping relationship between the position update and the value of the objective function by simulating the feeding behavior of humpback whales, and its optimization principle is to map the global optimal solution to the position of the prey, and to adjust the spatial distribution of the population to approximate the optimal solution through iteration, which is mainly divided into three phases: encircling predation phase, bubble net attacking phase, and global exploratory phase [14].

In the whale optimization algorithm, the quality of the initialized population affects the convergence speed and global search ability of the algorithm. Traditional random initialization may lead to uneven distribution or insufficient diversity of the population [15]. In this paper, we propose a chaotic and adversarial learning based strategy, which uses chaotic mapping to initialize the population, then performs adversarial learning on the chaotic population, and finally combines the two populations. For an initial random number in $[0,1]$, the chaotic Tent mapping is given by:

$$T(r) = \begin{cases} 2r & 0 \leq r \leq \frac{1}{2} \\ 2(1-r) & \frac{1}{2} \leq r \leq 1 \end{cases} \quad (5)$$

Chaotic sequences are first generated by Tent mapping and then mapped to the search space:

$$x_{chaotic} = lb + (ub - lb) \cdot T(r) \quad (6)$$

where lb is the lower bound of the search space; ub is the upper bound of the search space; and $x_{chaotic}$ is the chaotic individual. Subsequently, the generated chaotic individual is subjected to adversarial learning to generate an adversarial individual, as shown in equation (17):

$$x_{reverse} = lb + ub - x_{chaotic} \quad (7)$$

where $x_{reverse}$ is the generated opposing individual. Finally, the original chaotic population and the opposing population are combined according to a linear combination, and M individuals with the optimal fitness function value among them are selected as the new initial population, Eq:

$$x = \varepsilon \cdot x_{chaotic} + (1 - \varepsilon) \cdot x_{reverse} \quad (8)$$

where the parameter is a random number between $[0,1]$.

(1) encircling and preying stage

The location of each individual whale in the search space symbolizes a potential optimal solution. In this stage of the optimization process, the location of the optimal solution is unknown, the algorithm will mark the location of the candidate solution with the lowest fitness value as the current global optimal position, and other individual whales will adjust their positions according to this position and approach the optimal position. This process is mathematically modeled as:

$$\begin{cases} D = |CX^*(t) - X(t)| \\ X(t+1) = X^*(t) - AD \end{cases} \quad (9)$$

$$A = 2\alpha r_1 - \alpha \quad (10)$$

$$C = 2r_2 \quad (11)$$

$$\alpha = 1 + \cos(\pi \frac{t}{T_{max}}) \quad (12)$$

where t is the number of iterations; A and C are both coefficient variables; $X^*(t)$ is the target position; $X(t)$ is the current position; r_1 and r_2 are the random vectors in the interval $[0,1]$; the convergence factor is α and the maximum number of iterations is T_{max} .

In the actual optimization process, the linear optimization method cannot always meet the requirements of complex practical situations [16]. In view of this, a nonlinear control factor α is proposed, and this improvement is used to enhance the algorithm's optimization ability and performance performance, so as to make it more in line with the

requirements of practical application scenarios.

(2) Bubble Network Attack Phase

The process by which humpback whales release bubbles in order to form an encirclement and approach their prey through a spiral motion is known as the bubble net attack phase. The mathematical model of the spiral updating the position of an individual is as follows:

$$\begin{cases} X(t+1) = X^*(t) + D_1 \cdot e^{bl} \cos(2\pi l) \\ D_1 = |X^*(t) - X(t)| \end{cases} \quad (13)$$

where l is a random number in the interval $[-1,1]$; b

is a constant that determines the shape of the spiral; D_1 is the distance between the current whale position and the optimal position. In the traditional WOA, b adopts a fixed value, which leads to the population is prone to fall into premature convergence during global exploration and local exploitation, and the optimization search accuracy is limited. To improve this defect, an adaptive spiral parameter adjustment mechanism is proposed, where the dynamic adjustment factor 5 can autonomously update the predation path according to the iterative process, so that the spiral contraction rate changes adaptively with the number of iterations and balances the exploitation ability in different search stages, whose mathematical expression is shown in Equation (14):

$$b = \cos\left(\frac{\pi}{2}\left(1 - \frac{t}{T_{\max}}\right)\right) \quad (14)$$

In the Whale Optimization Algorithm model, individual

$$X(t+1) = \begin{cases} \omega \cdot X^*(t) - AD & p < 0.5 \\ \omega \cdot X^*(t) + D_1 \cdot e^{bl} \cos(2\pi l) & p \geq 0.5 \end{cases} \quad (17)$$

(3) Global Exploration Phase

When $|A| \geq 1$ and $p < 0.5$, the algorithm allows individual whales to perform global optimal solution exploration, in which case the whales randomly select a searching individual and update the positions of the other whales based on their positions, increasing the diversity of solutions. The mathematical model of the process is shown in the following equation:

$$\begin{cases} X(t+1) = X_{rand}(t) - AD \\ D = |CX_{rand} - X(t)| \end{cases} \quad (18)$$

where, $X_{rand}(t)$ is a randomly generated position vector of individual whales.

4. SEP Routing Protocol Based on Mixed Policy Whale Optimization

4.1. Position Mapping

In wireless sensor networks, the HWO algorithm may not match the actual node position after updating the node position. To solve this problem, position correction needs to be achieved by matching the optimized position with the actual node according to the proximity principle through the mapping mechanism based on Euclidean distance [18]. The specific formula is as follows:

$$P(X_{wp}) = \{X_n \mid \min[d(X_{wp}, X_n)], 1 \leq n \leq M\} \quad (19)$$

where, X_{wp} is the candidate optimal individual position;

whales shrink and encircle their prey while hunting in a spiral. To realize this mechanism, the algorithm introduces parameter P for determination. When the value of P is less than 0.5, the algorithm adopts the contraction encirclement mechanism; when the value of P is greater than or equal to 0.5, it performs spiral updating, and the specific expression is:

$$X(t+1) = \begin{cases} X^*(t) - A \cdot D & p < 0.5 \\ X^*(t) + D_1 \cdot e^{bl} \cos(2\pi l) & p \geq 0.5 \end{cases} \quad (15)$$

The whale optimization algorithm is constrained by its intrinsic inertia weights during implementation, resulting in a sluggish iterative process and poor optimization results [17]. To improve the performance of the algorithm in global search and local optimization, adaptive weights ω are introduced. At the initial stage of iteration, ω is set to a larger value to ensure that the algorithm has a strong global search ability; with the increase of iteration number, the value of weight ω is gradually reduced to a smaller value at the later stage of iteration, which ensures the algorithm's ability to search for the optimal solution in the local region and realizes a fine search of the local optimal solution. The adaptive weight ω is expressed as:

$$\omega = 0.3 - \ln\left(\cos\left(\frac{\pi(-t + T_{\max})}{3T_{\max}}\right)\right) \quad (16)$$

Applying the adaptive weights to the two phases of shrink-wrap and spiral approach, the mathematical model is as follows:

X_n is the actual node position; $d(X_{wp}, X_n)$ is the Euclidean distance between the optimal individual and the sensor node.

4.2. Setting the fitness function

Extending the network lifetime requires reducing the cluster head communication energy consumption and balancing the energy consumption of each node, this paper proposes a cluster head selection method based on the improved whale optimization algorithm, which takes into account the residual energy of the cluster head, the intra-cluster communication cost, and the communication cost between the cluster head and the terminal nodes, and optimizes the fitness function to achieve the maximization of the network life and the minimization of the energy consumption. The fitness function is set as follows:

(1) Objective function f_1 : Residual energy at the head of the cluster.

In wireless sensor networks, the cluster head node is responsible for managing the cluster members and performing data fusion, thus consuming high energy. In order to extend the network lifetime and optimize the performance, the energy consumption and management capability of the cluster head need to be considered in a comprehensive manner. The expression is as follows:

$$f_1 = \frac{1}{\sum_{i=1}^{M_{ch}} E_{current}(CH_i)} \quad (20)$$

where, M_{ch} is the optimal number of cluster heads; $E_{current}(CH_i)$ is the current cluster head residual energy, by minimizing f_1 , the node with higher residual energy can be obtained to be the cluster head.

(2) Objective function f_2 : Intra-cluster communication cost.

After the cluster head node is determined in the network, its surrounding nodes will choose the neighboring cluster head to join the cluster. In order to reduce the cost of intra-cluster communication, the node with smaller communication distance needs to be selected as the cluster head. f_2 expression is as follows:

$$f_2 = \sum_{i=1}^{M_{ch}} \frac{1}{n_i} \left(\sum_{j=1}^{n_i} d(j, CH_i) \right) \quad (21)$$

where, n_i is the number of neighbor nodes at the head of the cluster; $d(j, CH_i)$ is the distance between the cluster head and the neighbor nodes.

(3) Objective function f_3 : Communication cost between cluster heads and end nodes.

In wireless sensor networks, the distance from the cluster head to the base station has a significant impact on the network performance. The longer the communication distance, the more energy is consumed, so when selecting cluster heads, priority should be given to nodes close to the base station to reduce energy loss. In addition, in the stable communication phase of the network, the cluster heads need to forward the data to the base station. In order to reduce the inter-cluster communication cost, the node closer to the base station needs to be selected as the cluster head with the following expression:

$$f_3 = \frac{1}{\max \int_{i=1}^{M_{ch}} \frac{d_{\max} - d_i}{d_{\max} - d_{\min}}} \quad (22)$$

Where, d_i is the Euclidean distance between the cluster head and the terminal node; $d_{\max}$ is denoted as the maximum value of it; $d_{\min}$ is the minimum value.

Considering the above three factors together, the expression of the fitness function F_{fit} can be obtained as:

$$F_{fit} = \alpha f_1 + \beta f_2 + \gamma f_3 \quad (23)$$

where, α , β , γ are the weight coefficients of f_1 , f_2 , f_3 respectively, are random numbers between [0,1], and the three satisfy the relation $\alpha + \beta + \gamma = 1$. F_{fit} is the fitness function, and the energy consumption is lowest when the minimum value is taken. The flow of the improved cluster head election algorithm is shown in Fig. 1.

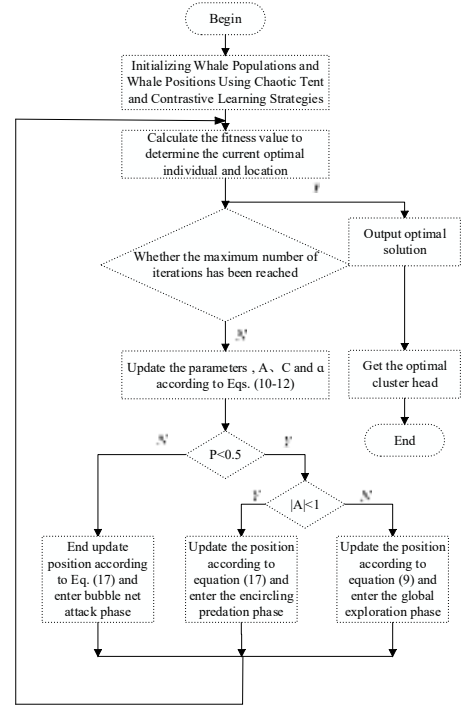


Fig. 1 Improved cluster head election process

5. Simulation results and comparative analysis

In order to verify the performance of HWO-SEP protocol, simulation experiments are conducted using MATLABR2023a. Four protocols, LEACH protocol, SEP protocol, WOA-SEP protocol and HWO-SEP protocol are simulated to compare and analyze the superior performance of the improved protocols.

5.1. Experimental parameter setting

Table 1 Simulation parameter settings

parameters	parameter value
Scope of monitoring	(100m×100m)
Base Station Location	(50,50)
Number of nodes	100
Packet length	4000bit
Number of simulation rounds	5000
Node initial energy	0.8J
ϵ_{fs}	10 pJ / (bit · m ²)
ϵ_{amp}	0.0013×10 ⁻³ pJ / (bit · m ⁴)
E_{elec}	50 nJ / bit

5.2. Analysis of experimental simulation results

The number of surviving nodes of HWO-SEP protocol with LEACH protocol, SEP protocol, and WOA-SEP protocol with the increase of simulation rounds is shown in Fig. 2, and the statistics of the first dead node and the first 50% node deaths are shown in Table 3. From Fig. 2, it can be found that the network stability of HWO-SEP has been effectively improved. Combined with the data in Table 3, the first dead node of HWO-SEP protocol appeared in 2135 rounds, LEACH protocol appeared in 1322 rounds, SEP protocol appeared in 1625 rounds, and WOA-SEP protocol appeared in 1835 rounds, which can be compared to the network stability of

HWO-SEP protocol, which was improved by 47.75%, 31.7%, and 31.7%, respectively. improved by 47.75%, 31.38%, and 16.35%. Thanks to the improved whale optimization algorithm, the cluster head election scheme of SEP protocol is optimized, and the multi-objective fitness function can carry out the optimal cluster head election according to the node's own situation, which reduces the phenomenon that some nodes die quickly due to the excessive energy consumption. In addition, HWO-SEP protocol has a longer survival period, i.e., the time interval from the start of operation until the death of all sensor nodes, which is effectively improved compared to LEAC, SEP, and WOA-SEP protocols.

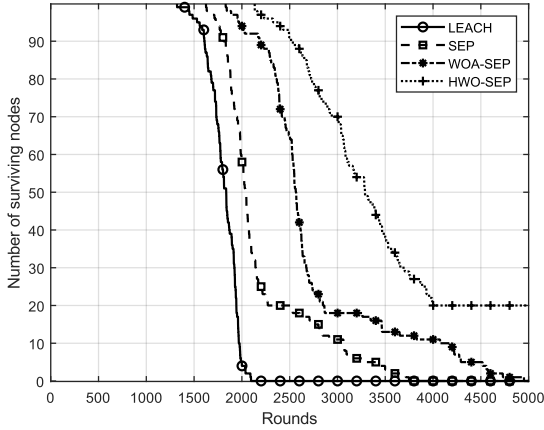


Fig. 2 Comparison of the number of surviving nodes in the monitored area

Table 2 Comparison of rounds of dead nodes in the monitoring area

	LEACH	SEP	WOA-SEP	HWO-SEP
First node death	1445	1625	1835	2135
10% node deaths	1607	1808	2184	2515
20% node deaths	1680	1884	2354	2724
30% node deaths	1735	1949	2419	3004
40% node deaths	1776	1988	2530	3084
50% node deaths	1836	2037	2564	3288

As shown in Fig. 3, the remaining energy of the nodes in the network decreases with the increase of rounds within 5000 rounds for the HWO-SEP protocol and is compared with LEAC, SEP, and WOA-SEP protocols. From the figure, it can be seen that the simulation curve of HWO-SEP protocol decreases more slowly, reflecting that the nodes consume less energy in each round, and the network life cycle is longer. HWO-SEP protocol introduces the improved whale optimization algorithm, the cluster head election is more reasonable, and the energy utilization is more balanced, which provides better performance.

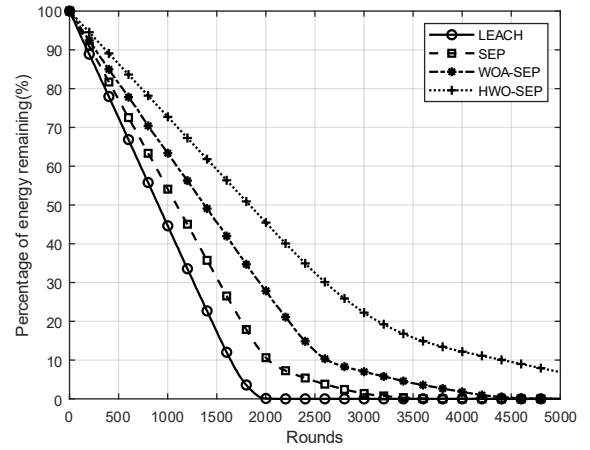


Fig. 3 Comparison of residual energy in the monitored area

As shown in Fig. 4, the simulation graph of the amount of data received by the end nodes reflects the ability of the network to collect data, which is an important index to judge the performance of the routing protocol. According to the curve in the figure, it can be learned that the HWO-SEP protocol maintains the highest number of packet delivery at the beginning of the network operation, and has a better data transmission capability. Influenced by the energy utilization efficiency, the improved protocol has more active nodes compared to other protocols, the end nodes receive more packets and the throughput of the network is higher.

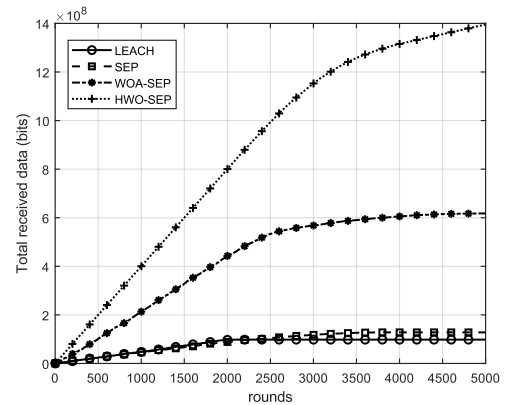


Fig. 4 Comparison of the volume of received data in the monitored area

6. Concluding Remarks

Aiming at the shortcomings of traditional SEP protocols in cluster head election optimization, this paper proposes a SEP routing protocol based on mixed-strategy whale optimization. Firstly: the global search ability of the algorithm is enhanced by initializing the population through hybrid strategy, and the diversity of the population is enhanced by using Tent mapping and adversarial learning strategy. Secondly, the linear convergence factor in the original algorithm is modified to a nonlinear convergence factor and a dynamic spiral parameter adjustment mechanism is introduced to construct an adaptive inertia weight model, which effectively balances the global exploration and local exploitation capabilities. Through the multi-objective fitness function, the cluster head election is transformed into a functional optimization problem by integrating the residual energy, intra-cluster communication cost and base station distance factor, and the optimal cluster

head selection is achieved by using the improved HWO algorithm. The simulation experiment process compares LEACH, SEP, WOA-SEP and the improved protocol of this paper in terms of the number of surviving nodes, the remaining energy of the network and the amount of data received by the terminal nodes, respectively, and the improved protocol shows better performance in all three aspects. The experiment verifies the stability of the improved protocol, and significantly improves the energy balance and network throughput capacity by dynamically optimizing the cluster head distribution.

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