Elite Niche Particle Swarm Optimization for Energy Clustering in Aeronautical Wireless Sensor Network

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Abstract. Recently, a wide variety of applications of aeronautical wireless sensor networks (AWSNs) make the clustering algorithm a paramount issue and bring profound changes to Internet of Things in AWSN-based applications. In AWSN, an energy-clustering algorithm is very significant to reduce the total energy cost of sensing data and solve the energy balance problem in AWSN. However, it is a challenging issue in AWSNs to have a low lifetime and energy utilization rate. In order to achieve a low energy consumption and further improve the lifetime of AWSNs, in this paper, we propose an elite niche particle swarm optimization (ENPSO), which combine the elite selection and niche sharing mechanism to develop the algorithm’s convergence rate and robustness. In the simulation, we compare the energy cost optimized by ENPSO with that optimized by grey wolf optimization (GWO) and simulated annealing (SA). Simulation results demonstrate that the energy cost optimized by ENPSO is 9.63% and 19.54% smaller than GWO and SA when the number of nodes is 100 with 10% cluster heads. It obviously shows that the performance of proposed ENPSO is better than other two algorithms and have a faster convergent rate and better robustness.

Keywords: Aeronautical wireless sensor networks, Particle Swarm Optimization, Clustering, Energy Cost

1. Introduction

Wireless sensor networks (WSN) is composed of a large number of micro sensors distributed in the monitored area, which can send the collected information to external monitoring personnel [1]. WSN is widely used in many fields, such as military, agriculture, personal health management, transportation, smart home, etc. It has become a research hotspot in above field in the world [2-3].

Aeronautical wireless sensor network (AWSN) is a significant branch of WSNs [4]. The node is mainly composed of four modules, including power module, processor module, wireless communication module and sensor module. In AWSN, each node can collect data and transmit data at the same time. An AWSN is composed of nodes using a self-organized way. The energy consumption consists of transmitting energy and receiving energy [5]. However, most of the nodes in the actual monitoring area are distributed in the complex and harsh environment. There is a problem that the batteries cannot be replaced in AWSNs. Once the energy of nodes is exhausted, they cannot work and it is difficult to replace them.

Sensors assembled in Aeroengine usually work in a bad environment, which will undergo large gradient changes in temperature and a large number of loads in a very short time, resulting in large alternating stress and severe vibration fatigue damage. Therefore, it is necessary to study the durability...
of the sensor in the stage of design.

In order to guarantee the lifetime as well as other performance indexes of the aircraft, ensure the flight safety and meet the comprehensive requirements of long life, high reliability, high attendance and low maintenance cost of the aircraft structure, it is significant to study the cluster head allocation optimization algorithm with low energy consumption.

Clustering problem is the most important problem in the applications of AWSN. It is also a hot topic in recent years [6-8]. The quality of clustering strategy directly affects the quality of network lifetime. Clustering technology is also an important mean to reasonably allocate resources and improve the energy efficiency of nodes and extend the network lifetime. Therefore, low energy clustering is an important goal of lifetime optimization design in AWSNs. Therefore, the research on low energy clustering is very important for WSN.

In [9], authors combined the energy heterogeneity of nodes with the classic LEACH protocol and proposed distributed energy efficient clustering method, which dynamically adjusted the parameters of the threshold of cluster head to improve the performance of WSN and reduce the energy cost of WSN. However, the robustness of system is not high. In [10], authors consider the transmission energy, distance and number of hops to build a multi-hop routing protocol, which can effectively reduce the energy consumption in the transmission stage, but the cluster head is still overloaded. In [11], authors consider the distance to the base station and the rest energy of the nodes to improve the number of cluster heads. However, there is still energy consumption imbalance. Many heuristic algorithms are also proposed to reduce the energy cost of WSN [12]. In [13], authors proposed a grey wolf optimization (GWO) scheme to save the energy consumption for better clustering scheme in WSNs. GWO can reduce network communication costs than SLM. The GWO is flexible but suffers from the problem of high computational complexity. In [14], authors proposed a simulated annealing (SA) scheme to save energy consumption in WSNs. In their work they improved energy efficiency without considering distance constraint. However, its convergence speed is slow when the quantity of sensor nodes is large.

In this paper, we propose an elite niche particle swarm optimization (ENPSO) to reduce the energy cost of WSN based on the traditional particle swarm optimization, which simulate the process of communication and foraging of firefly. The proposed algorithm combines the elite selection and niche sharing mechanism to improve the convergence speed and quality of solution. In the experience, we compare the results and performance of proposed method with GWO and SA with different number of nodes. Simulation results demonstrate that the ENPSO effectively reduce the total energy cost of system and improve the convergent speed of algorithm when the number of nodes is huge.

### 2. Problem Description and System model

Low energy adaptive clustering hierarchy (LEACH) is one of the typical clustering algorithms. However, it is impossible to guarantee the amount of cluster heads in each round. In the total lifetime of network, the network may have no cluster heads in the round. The main goal of the clustering problem is to reduce the energy consumption of aeronautical nodes in the network during data transmission, so that the nodes can work longer and the effective working time of the network can increase. The lifetime of AWSN is usually measured by the number of rounds of network running when the energy of first node is exhausted or that of last node is exhausted.

In this section, clustering model is given to calculate the total communication energy in AWSN. The circuit energy consumption of transmitting data and receiving data in AWSN is expressed by $E_{elec} \cdot k$. The energy consumption is directly proportional to the length of bits of data. $E_{elec}$ represents electronics energy parameter. In the transmission module, the energy consumption on the signal amplifier is also proportional to the data length and related to the distance of data transmission.

The energy consumption of transmitting $k$-bits data in the transmitting module is calculated in (1); energy consumption of receiving $k$-bits data in the receiving module is calculated in (2).
\[
E_t(k,d) = E_{elec} \cdot k + \varepsilon_{amp} \cdot k \cdot d^2
\]
(1)
\[
E_r(k) = E_{elec} \cdot k
\]
(2)
where \(E_t(k,d)\) represents the energy cost of transmitting \(k\)-bits data between two nodes with \(d\) meters. \(E_r(k)\) represents the energy cost of receiving \(k\)-bits data between two nodes. \(E_{elec}\) in transmitting circuit is equal to that in receiving circuit. \(\varepsilon_{amp}\) is the parameter of signal amplification. \(d\) is the communication distance between two nodes. \(d^2\) represents the channel transmission energy attenuation.

\[
E_{sum} = E_t + E_r
\]
(3)
Where \(E_{sum}\) represents the total energy cost of transmitting \(k\)-bits data and receiving \(k\)-bits data of a node. If there are \(N\) nodes in AWSN, the total energy cost of \(N\) nodes can be calculated in (4).

\[
R = \sum_{n=1}^{N} E_{sum}(n)
\]
(4)

3. Elite Niche Particle Swarm Optimization
Particle swarm optimization is an evolutionary algorithm based on swarm intelligence optimization. It was proposed by American social psychologist Kennedy in 1995 and inspired by the simulation of the migration and group behaviour of birds in the process of foraging [15]. The algorithm was found that birds can share the information about the location of food or target between birds, which can greatly improve the efficiency of finding food. Therefore, the cooperation between birds improves the search efficiency. At the same time, the fitness of population can be maximized. The search process of groups can be explained. When an individual searches for a certain target in the population, it usually adjusts the next search by referring to the individual currently in the optimal position in the population and the previous optimal position [16].

However, there are some defects in this algorithm, for example, it is easy to fall into local optimization and there are many optimized parameters, the coding scheme is not suitable for solving the energy consumption problem. This paper designs an elite niche particle swarm optimization, which combines elite selection and niche sharing mechanism, uses binary coding for the initial population, and improves the update strategy of particle swarm optimization, so that the algorithm can solve the problem more pertinently.

We assume that the search space is \(N\)-dimensional. there are \(M\) particles in the population. When the position of each particle is updated, the historical best position is taken into account. The steps of ENPSO are composed of population encoding, population initialization, fitness calculation, position updating of particles, termination condition.

3.1. Population encoding and Initialization
Assuming that the dimension of the population is \(N\) and the amount of the particles is \(M\). \(N\) also represents the amount of sensor nodes. In (5), the population can be expressed as \(Q=\{Q_1,Q_2,\cdots, Q_M\}\), where the position information of the \(m_{th}\) particle in the \(N\)-dimensional space can be expressed as \(Q_m=\{q_{m,1}, q_{m,2}, \cdots, q_{m,N}\}\). The corresponding speed can be expressed as \(V_m=\{v_{m,1}, v_{m,2}, \cdots, v_{m,N}\}\). \(q_{best}^m\) is used to represent the best position of the \(m_{th}\) particle, which records the best historical information of the particle during the whole searching period. The optimal location of the population is recorded as \(g_{best}\).

In clustering problem, the values in population represent the mode of sensors. In (6), the number of cluster heads in each individual is fixed. The particle position information is encoded by binary code.
Each \( q_{m,n} \) can only have two values, i.e. 0 or 1. When \( q_{m,n} = 1 \), the mode of sensors is cluster head. Otherwise, it represents a common node.

\[
Q = \begin{bmatrix}
q_{1,1} & q_{1,2} & \cdots & q_{1,N-1} & q_{1,N} \\
q_{2,1} & q_{2,2} & \cdots & q_{2,N-1} & q_{2,N} \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
q_{M-1,1} & q_{M-1,2} & \cdots & q_{M-1,N-1} & q_{M-1,N} \\
q_{M,1} & q_{M,2} & \cdots & q_{M,N-1} & q_{M,N}
\end{bmatrix}
\]  \hspace{1cm} (5)

\[
\sum_{n=1}^{N} q_{m,n} = K
\]  \hspace{1cm} (6)

3.2. Fitness calculation

The performance of individuals is evaluated by calculating fitness. Fitness represents the total communication cost of all cluster heads and common nodes in the process of transmitting and receiving data. Fitness can be calculated in (4) and we aim to find the individual with minimum energy cost. In (7), we aim to find the best individual in the population with the lowest energy cost.

\[
f = \min(R)
\]  \hspace{1cm} (7)

3.3. Position updating of particles

In PSO, the velocity updating of particle is also composed of three parts: velocity inertia, self-learning and social learning. The updating of particle position in the \((T + 1)th\) generation is determined by the position of the \(Tth\) generation and the velocity vector of the \((T + 1)th\) generation. The details are calculated in (8) and (9):

\[
v_{m,n}^{t+1} = \omega v_{m,n}^t + c_1 r_1 (p_{m,n} - q_{m,n}^t) + c_2 r_2 (q_{m,n}^t - q_{m,n}^*)
\]  \hspace{1cm} (8)

\[
q_{m,n}^{t+1} = v_{m,n}^{t+1} + q_{m,n}^t
\]  \hspace{1cm} (9)

Where \( m \) represents the particle and \( n \) represents dimension. \( v_{m,n}^{t+1} \) represents the velocity of particle in the \((T + 1)th\) generation. \( q_{m,n}^{t+1} \) represents the position of particle in the \((T + 1)th\) generation. \( \omega \) is inertia weight. \( t \) represents the iterations. \( c_1 \) and \( c_2 \) represent self-learning factor and social learning factor respectively. In general, \( c_1 = c_2 \). \( r_1 \) and \( r_2 \) are random number between 0 and 1. \( p_{m,n} \) represent the best position of \( m_{th} \) particle. \( q_{m,n}^* \) represents the best position in the population.

In ENPSO algorithm, the state of particle motion is defined from the perspective of probability. In the population, the \( q_{m,n} \) population is 0 or 1, \( v_{m,n} \) represents the probability. The formula of position updating is given in (10) and (11):

\[
q_{m,n} = \begin{cases} 
1 & \text{rand} \leq \text{Sig}(v_{m,n}) \\
0 & \text{rand} > \text{Sig}(v_{m,n})
\end{cases}
\]  \hspace{1cm} (10)

\[
\text{Sig}(v_{m,n}) = \frac{1}{1 + e^{-v_{m,n}}}
\]  \hspace{1cm} (11)

where \( \text{rand} \) is a random number, \( \text{rand} \in [0,1] \). \( \text{Sig} \) is a sigmoid function.
3.4. Termination condition
If the current number of iterations \( T < T_{\text{max}} \), recalculate energy cost and update the fitness of individuals. Otherwise, output the energy cost of the optimal particle and its cluster head allocation scheme.

3.5. Steps of ENPSO
This section gives the steps of ENPSO to optimize the allocation scheme of cluster heads.

Step1: Initialize parameters including number of individuals, maximum iteration, self-learning factor and social learning factor etc.

Step2: Randomly generate binary population \( Q \).

Step3: The fitness (energy cost) of each particle in the population is calculated, and the local optimal value \( p_{\text{best}} \) of each particle and the global optimal value \( g_{\text{best}} \) of all particles are obtained.

Step4: Update the position and velocity of each particle according to (9) and (10);

Step5: If the termination condition is met, Output the best individual and its energy cost. Otherwise turn to step 3.

4. Simulation and Results
In order to evaluate the performance of the ENPSO, a simulation program is designed with MATLAB R2014a. Without considering the random factors such as wireless channel interference and signal conflict, the AWSN with sensor nodes randomly distributed in 100m × 100m two-dimensional plane area is considered.

Assuming that some parameters are fixed. The number of data received or sent by each node is 1Mbps bits. The parameter of signal amplification is 100 \( pJ/\text{bit/m}^2 \). The electronics energy parameter is 50 \( nJ/\text{bit} \). The number of cluster head nodes is 10% of the total number of sensors.

In ENPSO, the number of particles is 80 and the maximum generation is 100. All nodes cannot move once placed. In order to better show the advantages of the ENPSO algorithm, GWO and SA are simulated and compared by MATLAB. In figure 1 and figure 2, 100 nodes and 500 nodes are randomly located in the monitored area respectively, where the black filled circle is the cluster head and the hollow circle is the common sensor. All of them are located in the in a square of 100 \( m^2 \).

![Figure 1. 100 nodes.](image1)

![Figure 2. 500 nodes.](image2)

Figure 3 and figure 4 show the comparation of energy consumption optimized by ENPSO, GWO and SA with different number of sensor nodes when the amount of cluster heads is 10% of the total number of sensors. In figure 3, there are 100 nodes in the sensing area. At the beginning of the iteration. The optimization speed of the three algorithms is very fast. In the last 50 generations, the convergence speed of the algorithm becomes slow. However, the ENPSO have a higher convergence
rate than GWO and SA. After 100 generations, the energy consumption optimized by ENPSO is 70.69J and that optimized by GWO and SA are 78.22J and 87.73J respectively. Results demonstrate that the energy cost optimized by ENPSO is 9.63% and 19.54% smaller than GWO and SA when the number of nodes is 100 with 10% cluster heads.

\[ \text{Energy Cost} = 70.69 \text{J for ENPSO, 78.22J for GWO, 87.73J for SA} \]

\[ \text{Reduction} = 9.63\% \text{ and } 19.54\% \text{ for ENPSO} \]

In figure 4, when the number of sensor nodes is 200, the energy cost optimized by ENPSO, GWO and SA are 114.64J, 129.72J and 148.60J respectively. It can be seen from the data that the communication quality has been significantly improved.

\[ \text{Energy Cost} = 114.64 \text{J for ENPSO, 129.72J for GWO, 148.60J for SA} \]

\[ \text{Reduction} = 9.63\% \text{ and } 19.54\% \text{ for ENPSO} \]

It is proved that the ENPSO algorithm based on low energy clustering can effectively rationalize the location distribution and the number of cluster heads, and finally reduces energy consumption of sensor and prolongs network lifetime.

5. Conclusions
In this paper, in order to improve the performance and convergence speed, we introduce the main idea of ENPSO and give the implementation process of the algorithm. It combines elite selection and niche sharing mechanism, which can increase the diversity of the population and improve the ability of the ENPSO to avoid falling to the local optimization, and further enhance the global search ability. In the simulation, we compare the energy cost optimized by ENPSO with GWO and SA with different amount of aeronautical sensor nodes. Experiment results show that ENPSO have better effectiveness to reduce the energy cost of transmitting data and receiving data. It has a high convergent rate in finding global optima.

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