A many-objective optimization WSN energy balance model

Di Wu[1], Shaojin Geng[1], Xingjuan Cai[1*], Guoyou Zhang[1] and Fei Xue[2]

1 Taiyuan University of Science and Technology, Complex System and Computation Intelligent Laboratory

Taiyuan, Shanxi 030024 - China.

[e-mail: wuxiaodou942@163.com, shaojin_geng@163.com, xingjuancai@163.com, guoyouzh@sohu.com]

2 Beijing Wuzi University, School of Information

Beijing, 101149 - China

[e-mail: xuefei2004@126.com]

*Corresponding author: Xingjuan Cai

Abstract

Wireless sensor network (WSN) is a distributed network composed of many sensory nodes. It is precisely due to the clustering unevenness and cluster head election randomness that the energy consumption of WSN is excessive. Therefore, a many-objective optimization WSN energy balance model is proposed for the first time in the clustering stage of LEACH protocol. The four objective is considered that the cluster distance, the sink node distance, the overall energy consumption of the network and the network energy consumption balance to select the cluster head, which to better balance the energy consumption of the WSN network and extend the network lifetime. A many-objective optimization algorithm to optimize the model (LEACH-ABF) is designed, which combines adaptive balanced function strategy with penalty-based boundary selection intersection strategy to optimize the clustering method of LEACH. The experimental results show that LEACH-ABF can balance network energy consumption effectively and extend the network lifetime when compared with other algorithms.

1. Introduction

With the rapid advancement of modern technology, the expansion of the information world and Internet of Things has spawned a wireless sensor network (WSN) [1]. WSN is self-organizing multi-hop network system composed of thousands of micro-low-power sensor nodes scattered and a sink node of wireless communication. For the characteristics of WSN, an efficient low-power routing protocol is researched and designed, which can save energy consumption (EC) and increase network lifetime. According to the topology structure, wireless sensors are classified into a planar routing protocol [2] and a hierarchical routing protocol (cluster routing protocol) [3]. As the important research branch of WSN routing protocols, clustering routing protocols has the advantages of high energy utilization, clear node division, easy management of network topology, simple data fusion operation and easy system expansion, which makes the current WSN routing protocol become the key directions and hotspots of research.

The clustering routing protocol divides the network into multiple small areas according to the specific algorithm. Each area is referred to as a cluster, and each cluster is generally composed of a cluster head node (CHN) and many cluster member nodes (CMN). The CMN are responsible for sensing the information of the monitored area, and then transmitting the collected information to the CHN in the designated time slot. At last, the CHN is responsible for collecting the information and performing data fusion operations to forwarding to the sink node. The CMN usually turn off the wireless communication module in the transmission time slot that does not belong to itself in order to reduce EC. The clustering structure is not only beneficial to the application of distributed algorithms [4], but also suitable for large-scale network applications [5]. It is difficult to design an efficient data transmission mechanism is of great significance for WSN. The Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol proposed by Heinzelman et al [6]. Kulik proposes SPIN [7] protocol and Ossama proposes HEED [8] protocol. Due to the LEACH as the first clustering routing protocol has the performance of simple, flexible, energy efficient and extensible. It also highlights the role of data fusion. Many clustering routing protocols are inspired by the clustering idea of the protocols. Therefore, the choice of LEACH protocol for research has certain advantages and typicality. Scholars have proposed different ways to improve their shortcomings, and achieved corresponding results. The LEACH-C protocol [9] by using the sink node as the central control node. The protocol considers the distance from the CMN to the CHN in the cluster head elective. In LEACH-EO [10], the remaining energy of the node is considered in the cluster head election and the communication mechanism of each cluster is charged from single-hop to multi-hop. LEACH-HD [11] proposed the idea of regional division. The cluster head of this area is selected, which is characterized by the largest residual energy. And multi-hop communication is adopted between cluster heads.
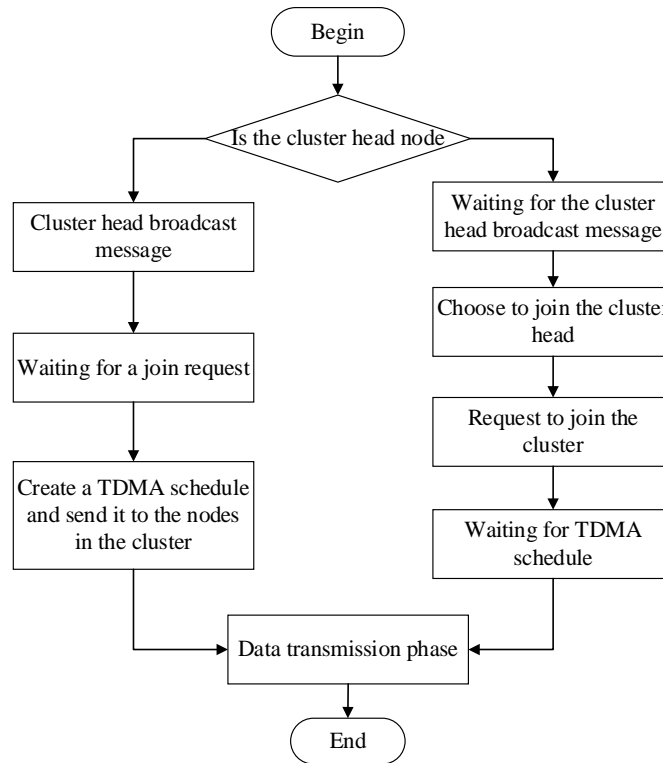
Fig. 1. The flow chart of LEACH protocol

The LEACH protocol [12] is cyclically executed in units of "rounds". Each round consists of two phases, the details are showed in **Fig. 1**, including the cluster formation and the data transmission. Each cluster is consisted of one CHN and several CMNs, which are self-organized during the formation of the cluster. The CMN communicates with its own CHN, while the CHN is responsible for receiving data from all CMNs and transmitting the data to the sink node. In the data transmission process, a combination of routing algorithms and data fusion technology can reduce the amount of network data forwarding. However, the protocol uses single-hop communication between clusters and within the cluster leading to the energy consumption resource of the CHN is relatively high, which may affect the network lifetime. What's more, the rationality of CHN selection is an important problem, which can achieve the purpose of extending the network lifetime. Therefore, a many-objective optimization WSN energy balance model is established.

In recent years, Many-objective Optimization Problems (MaOPs) [13] has become a major research hotspot. The MaOPs mainly refers to the objective number with more than four [14]. There are many pareto optimal solutions, and it is impossible to find all pareto optimal solutions. The many-objective optimization algorithm (MaOEA) can use fitness function to guide the population to close the Pareto Front (PF). Therefore, two aspects should be considered in designing the algorithm. On the one hand, the convergence of the algorithm

[15] which is a process of approaching the pareto optimal solution set constantly. On the other hand, the distribution of the algorithm [16] which is that the non-dominant solutions are distributed as uniformly and broadly as possible in the objective function space. Based on the above problems, some scholars have achieved outstanding results in solving MaOPs. Typical MaOEAs can be divided into three categories according to different selection mechanisms [17].

    a. The MaOEAs based pareto dominance. The convergence of the algorithm is guaranteed by pareto dominance, and diversity preservation mechanism is designed to ensure the diversity of the selection, such as NSGA-III [18] and NSGAIII-NE [19].

    b. The MaOEAs based decomposition strategy. The core is to transform the many-objective optimization problem into multiple single-objective sub-problems, and output a set of pareto optimal solution simultaneously. Typical algorithms include MOEA/DD [20] and EFRRR [21].

    c. The MaOEAs based performance evaluation index. Such as HypE [22] and IBEA [23]. By predicting the real PF, the corresponding performance evaluation index values were calculated.

Although the above algorithms balance diversity [24] and convergence [25] to some extent, there are corresponding problems in each algorithm. For example, parameter design is a very random factor. In order to overcome the shortcomings of MAOEA and optimize the choice of cluster head node, a many-objective optimization algorithm LEACH-ABF is designed. The contribution includes the following two points: (1) The many-objective optimization WSN energy balance model is designed to better balance the energy consumption and extend the network lifetime. (2) In order to optimize the model, the LEACH-ABF is proposed which combine the adaptive balance function strategy, genetic operation and penalty-based boundary selection intersection strategy.

The rest of this paper is described as follows: Section 2 introduces the related work of LEACH. And the many-objective optimization WSN energy balance model is designed in Section 3. Section 4 gives the detailed flow of the algorithm LEACH-ABF. Section 5 verifies the performance of the proposed algorithm through the standard test suite DTLZ. And the algorithm has better performance on LEACH by comparing with other different algorithms. Finally, the conclusion is provided in section 6.

2. The related work

In recent years, clustering protocol in WSN has been extensively studied. As the first clustering routing protocol, LEACH proposed the concept of network clustering. The main idea is dividing the network into clusters with different sizes, and the nodes are elected as the cluster heads to balance the energy consumption (EC) of the network effectively. The network topology [26] of the LEACH protocol is shown in **Fig. 2**, the network is represented

by three clusters, red represents the cluster head node (CHN) and green represents the cluster member node(CMN). The sink node is the core of the entire network and is represented by black signal tower.
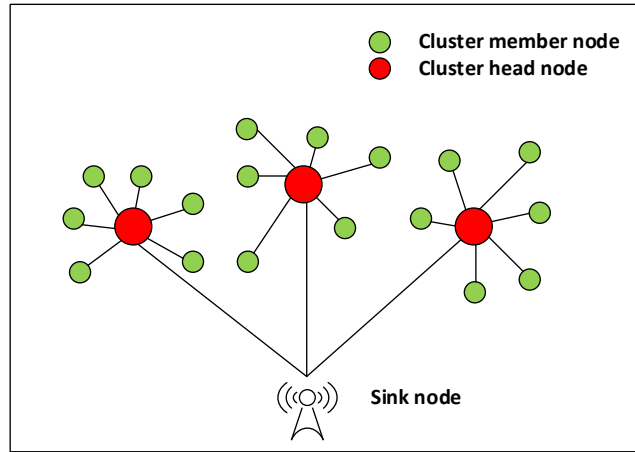

Fig. 2. The network topology of the LEACH protocol

In **Fig. 2**, the LEACH protocol also has problems such as clustering unevenness, cluster head election randomness and single-hop within the cluster. Domestic and foreign scholars have proposed swarm intelligence algorithm [27-29] and intelligent optimization algorithm [30, 31] to optimization the performance of LEACH, and achieved corresponding results. Cui et al [32] proposed a bat algorithm (BA) [33, 34] combined with centroid strategy to optimize the LEACH protocol. In [35], the concept of advanced nodes and an enhanced cluster head election rule set are used to optimize the LEACH protocol, and the meta-heuristic particle swarm enhancement algorithm is used to initially cluster the sensor nodes. Cai [36] proposes an improved FTBA algorithm for fusion curve strategy, which improves local and global search ability to select cluster heads to extend the lifetime of the network. Jourdan [37] used genetic algorithm to optimize the energy of WSN for the first time. The binary code was used to divide the nodes into CHN and CMN. Then, the genetic algorithm was used to select the optimal chromosomes, and the optimized network is obtained by chromosome decoding. In [38], generic algorithms are used as an optimization method for sensor networks by introducing a special node-inactive point, which does not participate in network communication. From the above literature research, there are two aspects can be improved for LEACH algorithm.

(1) Keep traffic load balance [39]

Design a more efficient routing protocol to avoid unnecessary energy consumption. By spreading the data transmission task to balance the network EC and delay the node to die prematurely for each node.

(2) Reduce traffic to save energy

Design an efficient wireless sensor node deployment to avoid data communication EC due to data redundancy. Use the corresponding algorithm to minimize data traffic and avoid redundant data transmission. Thus, achieving the purpose of extending the entire lifetime.

LEACH faces many challenges in its research and development process, although it has enormous application potential and value. For example, the relative residual energy and cluster uniformity between nodes are not dynamically considered when the network is clustered. When multi-hop communication [40] is adopted between clusters, the protocol does not consider the optimization of the overall energy consumption of the network. These limitations make the lifetime of LEACH very limited, which seriously hinders the development and application of LEACH. It can be seen that the previous paper only optimized one or two goals, and did not consider optimizing the LEACH protocol from multiple perspectives. Therefore, it is an urgent problem to use energy efficiently and extend the lifetime of LEACH. In this paper, the LEACH protocol is selected for detailed research and analysis, and the cluster head election algorithm is improved. The sink node distance, cluster distance, the overall energy consumption of the network and the network energy consumption balance are used to select cluster nodes, which can reduce the EC caused by information transmission in WSN and balance the distribution of CHN in the network. On this basis, data fusion technology is introduced in the data transmission phase of the protocol to reduce the amount of data forwarding, reduce the EC of nodes, and extend the lifetime of the network.

3. WSN Model

3.1 Model hypothesis

In order to facilitate further study of LEACH protocol, it is necessary to make the following assumptions about the network model of LEACH protocol [41].
  (1) Wireless sensor networks are small and medium-sized with fixed sink nodes.
  (2) There is only one sink node in the network. The computing power, storage capacity and energy resources of the sink node are generally unlimited. And the sink node can obtain the location information, energy information and ID information of each node.
  (3) Nodes are randomly distributed in a 100*100m work area, each node has a unique ID.
  (4) Nodes have the same physical structure and initial energy, computing power, and storage capacity.
  (5) The node is fixed and can communicate with the sink node either directly or indirectly.
  (6) After the network clustering is formed, not only the single-hop communication mode is utilized between the cluster head node (CMN) and the cluster head node (CHN), but also between the CHN and the sink node.

3.2 WSN Energy Balance Many-objective Optimization Model

The randomness generated by the CHN in the LEACH protocol cannot guarantee the rationality of the CHN position. Unbalanced cluster head distribution consumes a lot of energies of CHN. Both of them will affect the lifetime of the entire network. In order to select the CHN, the four objectives is discussed: the distance from CMN to cluster nodes (cluster distance), the distance from cluster nodes to sink nodes (sink node distance), the overall energy consumption (EC) of the network and the network energy consumption balance, which are optimized as many-objective optimization algorithms [42].

(1) Cluster distance D_{nc}

In the WSN, the CMN needs to send information to the CHN. When the CMN in each cluster surround the cluster head, that means the distance between the CMN and the CHN is the closest, and the transmission distance is the shortest. Under this circumstance, the EC of CMN is the least. The cluster distance model is showed as follows:

$$D_{nc} = \min(\sum_{m=1}^{M} (\sum_{n=1}^{N} d_{ncluster}))$$
(1)

where, M represents number of CHN, N represents number of CMN of each cluster and $d_{ncluster}$ represents Euclidean distance from CMN to CHN.

(2) Sink node distance D_{cs}

In the LEACH protocol, the CHN performs data fusion on the received information and sends it to the sink node. The shorter the transmission distance, the less the EC.

$$D_{cs} = \min \sum_{m=1}^{M} d_{csink}$$
(2)

where, d_{csink} represents Euclidean distance from cluster node to sink node.

(3) Overall energy consumption of the network $Energy1$

The overall EC of the network in the clustering stage as follows.

Firstly, CHN broadcasts a message that it is the cluster head and transmits a TDMA schedule. The table is sent to the CMN, and the amount of data is t bit. The EC of CHN sends information is $E_{cn}(t, d_{cn})$.

$$E_{cn}(t, d_{cn}) = \begin{cases} t(E_{elec} + \tau_f d_{cn}^2), & d_{cn} < d_0 \\ t(E_{elec} + \tau_m d_{cn}^4), & d_{cn} \geq d_0 \end{cases}$$
(3)

where, E_{elec} is the EC by the node to transmit 1 bit of data, τ_f and τ_m respectively represent the EC of the signal amplifier when transmitting 1 bit of data per unit distance in the free space and multipath fading models. d_{cn} represents the Euclidean distance from

current cluster member to CHN. Threshold $d_0 = \sqrt{\tau_f / \tau_m}$ for conversion between communication channel models.

And then, the cluster member node accepts the t bit information and TDMA table from the CHN and sends the t bit data to the CHN according to the TDMA table. In this process, the EC by the CMN $E_{non-cn}(t, d_{cn})$ is as follows:

$$E_{non-cn}(t, d_{cn}) = \begin{cases} t(E_{elec} + \tau_f d_{cn}^2) + t \times E_{elec}, & d_{cn} < d_0 \\ t(E_{elec} + \tau_m d_{cn}^4) + t \times E_{elec}, & d_{cn} \geq d_0 \end{cases} \tag{4}$$

Finally, the EC of the process for CHN accept the CMN sends the information $E_{cn}(t, d_{cn})$:

$$E_{cn}(t, d_{cn}) = tE_{elec} \times (\frac{N}{M} - 1) \tag{5}$$

In summary, the overall EC of the network $Energy1$ in the clustering stage is summed by Eq. (3)-(5).

$$Energy1 = \begin{cases} \min(tE_{elec} \times (\frac{N+2}{M} - 1) + t\tau_f d_{cn}^2 \times (\frac{N}{M} + 1)), & d_{cn} < d_{\ell} \\ \min(tE_{elec} \times (\frac{N+2}{M} - 1) + t\tau_m d_{cn}^2 \times (\frac{N}{M} + 1)), & d_{cn} \geq d_{\ell} \end{cases} \tag{6}$$

(4) Network energy consumption balance $Energy2$

The network EC balance is composed of two parts D_{no} and D_{en}. The variance of the number of CMN in each cluster D_{no} is as follows. The smaller the value, the more average the number of nodes in each cluster, which means that the load per cluster head is more balanced.

$$D_{no} = \frac{\sum_{i=1}^{m} (v_i - u)^2}{m} \tag{7}$$

where v_i is the number of CMN in the $i-th$ cluster, u is the average number of CMN of each cluster in the network.

The variance of the EC of clustered member modes in each cluster is D_{en}. The value is smaller, the more average the EC in the clusters. The equation is:

$$D_{en} = \frac{\sum_{i=1}^{m} (E_i - u_e)^2}{m} \tag{8}$$

where E_i is the total EC in the $i-th$ cluster and u_e is the average of the EC of each cluster.

In summary, the network EC balance is:

$$Energy2 = \min(D_{no} + D_{en}) \tag{9}$$

4. LEACH-ABF Algorithm

Aiming at the cluster head optimization problem of WSN, a many-objective optimization algorithm LEACH-ABF based on adaptive balance function is proposed. It is applicable for our proposed wireless sensor network energy balance optimization model. The algorithm flow of LEACH-ABF includes three parts: the proposed adaptive balance function strategy, genetic operation, and penalty-based boundary intersection selection strategy, which are respectively introduced in section 4.1 to 4.3. Finally, the framework of the algorithm is presented in section 4.4.

4.1 Balance function strategy

Inspired by [43], this function is adaptively combined with the diversity function and the convergence function to increase the selection pressure and make the solution to the true PF. Assume that the population $X = \{x_1, x_2, ..., x_N\}$ consists of N individuals. For each individual x, the calculation method of ABF value is as follows:

$$ABF(x_i, X) = \lambda \times DF(x_i, X) + \sigma \times CF(x_i, X) \tag{10}$$

where, $DF(x_i, X)$ and $CF(x_i, X)$ represent the normalized diversity and convergence of the population, respectively. λ and σ are two weight vector that impact the diversity and convergence of algorithm adaptively. This strategy can help us to choose a better solution.

Specifically, the normalized diversity function $DF(x_i, X)$ calculates individual distance from nearest neighbors. The greater the distance, the better the diversity of the population. And the formula is as follows:

$$DF(x_i, X) = \frac{S(x_i) - S_{min}}{S_{max} - S_{min}} \tag{11}$$

where, $S(x_i)$ [44] represents the shifted Euclidian distance to the nearest neighbor:

$$S(x_i) = \min_{x_j \in X, j \neq i} \sqrt{\sum_{b=1}^{a} s(f_b'(x_i), f_b'(x_j))^2} \tag{12}$$

$$s(f_b'(x_i), f_b'(x_j)) = \begin{cases} f_b'(x_j) - f_b'(x_i) & if \ f_b'(x_j) > f_b'(x_i) \\ 0 & otherwise \end{cases} \tag{13}$$

$$f_b'(x_i) = \frac{f_b(x_i) - f_b \min}{f_b \max - f_b \min} \tag{14}$$

where, $f_b'(x_i)$ is the $b-th$ normalized objective of x_i.

The convergence function $CF(x_p)$ represents the convergence capacities (Euclidean distance between $f_b'(x_i)$ and the ideal point $w = (0,0,...,0)$). The larger the value of CF, the closer the individual is to the ideal point. That means, the selection pressure that increases toward the ideal point, thus minimizing the objective function.

$$CF(x_p) = 1 - sqrt(\sum_{b=1}^{a}(f_b'(x_i) - w)^2)$$

(15)

4.2 Genetic operation

A new genetic operation that combines tournament selection, simulating binary intersections and polynomial variations, which are widely used to solve MaOPs and provide an effective search capability [45]. Firstly, the tournament selection is used to select excellent offspring from the parents. And then the parents produce excellent offspring by simulating binary crossover and polynomial variation. Through such an operation, we can achieve the purpose of selecting better convergence and diversity solutions.

4.3 Penalty-based boundary intersection selection strategy

The approach of the PBI selection [46] is used to improving population convergence and diversity. And the main idea of strategy is defined as follows:

$$\min \quad B^{pbi}(x \mid q^*, e^*) = p_a + \partial p_b$$
$$\text{subject to } x \in \Omega$$
$$p_a = \frac{\left\| (Fit(x) - z^*)^T q^* \right\|}{\left\| q^* \right\|}$$
$$p_b = \left\| Fit(x) - (e^* + p_a \frac{q^*}{\left\| q^* \right\|}) \right\|$$

(16)

where, e^* is the ideal point, q^* represents the reference point and ∂ is the adaptively defined penalty parameter. The value of ∂ is five according to [46]. Also, p_a and p_b are used to evaluate the convergence of x towards efficient front and measure the diversity of population, respectively. The procedure of PBI selection operation is presented in **Algorithm 1**. Firstly, non-dominated sorting operations is performed in order to layer the population L, then the objective function is normalized. The obv is obtained by calculating the vertical distance between the reference point and the population to associate population with reference point and perform PBI calculations. Finally, niche operations are used to gain population P.

Algorithm 1: The main procedure of PBI selection operation

Begin
Input: population off, reference points q^*
$\quad\quad\quad L$ = Non-dominated sort (off)
$\quad\quad\quad ob$ = Normalize objectives (L)
$\quad\quad\quad obv$ = Associate (ob, v)
$\quad\quad\quad r$ = PBI (obv)
$\quad\quad\quad P$ = Niche (r)
$\quad\quad$ End
Output: population P
End

4.4 Framework of the LEACH-ABF

Algorithm 2 shows the framework of the LEACH-ABF. First, the parameters of the algorithm are initialized. And the objective function value is calculated by the wireless sensor energy balance model. Then, an adaptive balance function operation on the objective function value is performed to generate an archive $Arch$. Meanwhile, the genetic operator is used in the population P to produce excellent offspring off. The $Arch$ and the off is combined to update the external archive, and then, the $Arch$ perform genetic operations to generate a new solution S. Finally, output the best solutions by updating the population with the ABF strategy.

Algorithm 2: The main framework of LEACH-ABF

Begin
$\quad\quad$ Initial the population P, the reference point q^*
$\quad\quad Z_{min}$ =min (P)
$\quad\quad$ While Global Not Termination (P)
$\quad\quad\quad\quad Q$ = balance function (P)
$\quad\quad\quad\quad off$ = Genetic operator (Q)
$\quad\quad\quad\quad Z_{min}$ = min (Z_{min}, off)
$\quad\quad\quad\quad P$ = PBI selection (off)
$\quad\quad$ End
$\quad\quad$ Output the population P
End

4.5 Computational Complexity of LEACH-ABF

This section will analyze the time complexity of the designed LEACH-ABF algorithm. The components of algorithm include population initialization, definition of reference point, balance function operation, genetic operation and PBI calculation. Suppose the population size is N, the objective dimension is M and the number of reference points is H. The time complexity of defining the reference point of Algorithm 1 is $O(MN)$, the balance

function requires $O(N^2)$ computations, and the time complexity of crossover and mutation for genetic operation is $O(MN^2)$, respectively. The PBI calculation operation includes non-dominated sorting, population normalization, association with reference points and niche processing operations. The time complexity of non-dominated sorting is $O(N^2 \log^{M-2})$, population normalization requires $O(N)$ calculations, population size is $2N$ and H reference points are associated with would requires $O(MNH)$ computations, and the time complexity of niche processing operations is $O(H)$. In summary, the algorithm complexity is $O(MN^2)$.

5. Simulation and Analysis

This section tests the algorithm in two aspects. The performance of the LEACH-ABF was first evaluated. In addition, the algorithm is applied to the energy balance many-objective optimization model of WSN and compared with other algorithms.

5.1 Algorithm Test and Analysis

DTLZ [47] problems are non-convex, multi-modal, non-connected and non-uniform Pareto front. The simulation results of LEACH-ABF are provided on 4 to 15 objective optimization problems. In the evaluation criterion, the inverse generational distance (IGD) is chose as the performance metric, evaluate the quality of the solution which can provide a combination of information about the convergence and diversity. The reference point generation scheme in NSGAIII is used to construct the reference set on the hyperplane. The IGD value is obtained as follows:

$$IGD(A,Z) = \frac{1}{|Z|} \sum_{i=1}^{|z|} \min_{j=1}^{|A|} d\left(z_i, a_j\right) \tag{17}$$

where $d\left(z_i, a_j\right) = \left\| z_i - a_i \right\|_2$. The smaller the IGD value is, the closer the solution set to the PF.

To test the fairness of the algorithm process, the parameter of algorithm is set as follows: for each algorithm, the number of iterations is 10000 generations, running 30 times independently, the best, median and worst IGD values are reported. For all algorithms, performance metrics are computed using the final solution set. **Table 1** shows different population sizes corresponding to different number of objectives. **Table 2** shows the LEACH-ABF algorithm, which compares with other three common algorithm on DTLZ test suite. The best results (average minimum) are marked with blue. In each test case, the symbol '+/-/= 'shows the performance of good, poor and medium for other three algorithm to the LEACH-ABF.

Table 1. Different dimensions correspond to different population sizes

Population size	Number of objectives
120	4
132	6
156	8
274	10
135	15

Table 2. The IGD value obtained by four algorithms with different number of objectives

Problem	N	M	NSGAIII	KnEA	EFRRR	LEACHABF
DTLZ1	120	4	5.3275×10^{-1} (3.39×10^{-1}) -	3.2772×10^{-1} (2.65×10^{-1}) =	1.2959×10^{0} (4.62×10^{-1}) -	3.2380×10^{-1} (2.74×10^{-1})
	132	6	1.0944×10^{0} (5.56×10^{-1}) -	9.8161×10^{-1} (5.26×10^{-1}) -	3.1453×10^{0} (1.52×10^{0}) -	3.6678×10^{-1} (2.24×10^{-1})
	156	8	1.8303×10^{0} (7.55×10^{-1}) -	4.3781×10^{0} (1.85×10^{0}) -	1.0356×10^{0} (6.66×10^{-1}) -	5.8657×10^{-1} (3.06×10^{-1})
	274	10	3.5126×10^{0} (1.67×10^{0}) -	2.5422×10^{0} (1.61×10^{0}) -	1.5274×10^{0} (4.72×10^{-1}) -	7.8875×10^{-1} (4.12×10^{-1})
	135	15	1.6505×10^{0} (8.07×10^{-1}) -	8.1788×10^{0} (7.44×10^{0}) -	5.9969×10^{-1} (2.99×10^{-1}) =	7.6379×10^{-1} (4.34×10^{-1})
DTLZ2	120	4	1.2366×10^{-1} (4.42×10^{-4}) -	1.4025×10^{-1} (3.86×10^{-3}) -	1.3032×10^{-1} (1.43×10^{-3}) -	1.2317×10^{-1} (4.69×10^{-4})
	132	6	2.7361×10^{-1} (3.84×10^{-3}) -	2.8004×10^{-1} (5.10×10^{-3}) -	2.8880×10^{-1} (4.71×10^{-3}) -	2.7305×10^{-1} (4.99×10^{-2})
	156	8	4.1324×10^{-1} (8.64×10^{-2}) -	3.8137×10^{-1} (1.16×10^{-2}) +	3.8973×10^{-1} (5.82×10^{-3}) -	3.8871×10^{-1} (9.41×10^{-2})
	274	10	5.8423×10^{-1} (9.21×10^{-2}) -	4.5441×10^{-1} (1.42×10^{-2}) =	4.9015×10^{-1} (1.26×10^{-2}) =	4.9360×10^{-1} (6.57×10^{-2})
	135	15	7.5253×10^{-1} (5.36×10^{-2}) -	6.1423×10^{-1} (1.30×10^{-2}) +	5.7655×10^{-1} (1.37×10^{-2}) +	6.9629×10^{-1} (4.35×10^{-2})
DTLZ3	120	4	2.2288×10^{1} (7.24×10^{0}) -	1.1970×10^{1} (4.62×10^{0}) -	4.1493×10^{1} (1.26×10^{1}) -	8.4369×10^{0} (2.97×10^{0})
	132	6	4.8324×10^{1} (1.27×10^{1}) -	4.1066×10^{1} (1.13×10^{1}) -	8.6937×10^{1} (1.74×10^{1}) -	1.8500×10^{1} (8.03×10^{0})
	156	8	8.1609×10^{1} (2.54×10^{1}) -	1.1961×10^{2} (3.65×10^{1}) -	5.2031×10^{1} (1.37×10^{1}) -	2.5701×10^{1} (9.27×10^{0})
	274	10	1.3664×10^{2} (3.29×10^{1}) -	1.2173×10^{2} (3.98×10^{1}) -	8.0790×10^{1} (1.70×10^{1}) -	5.0361×10^{1} (1.29×10^{1})

	135	15	1.4947×10^{2} (5.85×10^{1}) -	2.6338×10^{2} (1.29×10^{2}) -	3.7671×10^{1} (1.21×10^{1}) =	4.0033×10^{1} (1.97×10^{1})
DTLZ4	120	4	2.1243×10^{-1} (1.48×10^{-1}) =	1.6724×10^{-1} (8.21×10^{-2}) =	1.5194×10^{-1} (8.46×10^{-2}) =	3.7205×10^{-1} (2.16×10^{-1})
	132	6	2.9429×10^{-1} (6.56×10^{2}) =	4.0279×10^{-1} (1.18×10^{-1}) =	2.7577×10^{-1} (2.93×10^{-2}) =	3.9409×10^{-1} (1.28×10^{-1})
	156	8	4.1171×10^{-1} (6.58×10^{-2}) =	4.4686×10^{-1} (4.56×10^{-2}) =	3.6589×10^{-1} (1.83×10^{-2}) =	4.6133×10^{-1} (1.01×10^{-1})
	274	10	5.9363×10^{-1} (8.01×10^{-2}) -	5.4144×10^{-1} (1.51×10^{-2}) -	4.7900×10^{-1} (5.91×10^{-3}) =	5.2096×10^{-1} (5.73×10^{-2})
	135	15	8.1795×10^{-1} (1.01×10^{-1}) -	6.4380×10^{-1} (6.71×10^{-3}) +	6.3326×10^{-1} (5.53×10^{-3}) +	7.3213×10^{-1} (2.99×10^{-2})
DTLZ5	120	4	5.2645×10^{-2} (1.64×10^{-2}) -	1.7168×10^{-1} (5.05×10^{-2}) -	1.1613×10^{-1} (2.50×10^{-2}) -	4.3794×10^{-2} (1.34×10^{-2})
	132	6	2.8065×10^{-1} (5.32×10^{-2}) -	3.1568×10^{-1} (1.30×10^{-1}) -	4.7667×10^{-1} (9.72×10^{-2}) -	1.5649×10^{-1} (5.70×10^{-2})
	156	8	2.6912×10^{-1} (1.38×10^{-1}) -	4.0479×10^{-1} (1.18×10^{-1}) -	3.3071×10^{-1} (6.64×10^{-2}) -	1.4851×10^{-1} (4.42×10^{-2})
	274	10	2.7063×10^{-1} (4.25×10^{-2}) -	3.7442×10^{-1} (1.15×10^{-1}) -	3.5588×10^{-1} (5.84×10^{-2}) -	2.4033×10^{-1} (3.70×10^{-2})
	135	15	3.1848×10^{-1} (5.85×10^{-2}) -	5.4605×10^{-1} (1.41×10^{-1}) -	3.0348×10^{-1} (5.54×10^{-2}) -	2.4324×10^{-1} (3.83×10^{-2})
DTLZ6	120	4	5.9183×10^{-1} (5.38×10^{-1}) -	6.4016×10^{-1} (3.82×10^{-1}) -	2.6597×10^{0} (5.32×10^{-1}) -	1.3374×10^{-1} (4.87×10^{-2})
	132	6	3.9959×10^{0} (8.05×10^{-1}) -	1.8090×10^{0} (5.39×10^{-1}) -	4.1741×10^{0} (8.17×10^{-1}) -	8.7525×10^{-1} (5.20×10^{-1})
	156	8	5.3346×10^{0} (6.56×10^{-1}) -	2.8578×10^{0} (4.62×10^{-1}) -	3.6570×10^{0} (6.86×10^{-1}) -	2.0514×10^{0} (5.85×10^{-1})
	274	10	6.5783×10^{0} (6.37×10^{-1}) -	3.2608×10^{0} (6.86×10^{-1}) =	5.7658×10^{0} (5.03×10^{-1}) -	3.4131×10^{0} (7.52×10^{-1})
	135	15	6.7800×10^{0} (5.57×10^{-1}) -	3.8873×10^{0} (4.60×10^{-1}) =	2.6351×10^{0} (7.18×10^{-1}) +	4.0780×10^{0} (8.74×10^{-1})
DTLZ7	120	4	3.4002×10^{-1} (6.75×10^{-2}) +	1.8760×10^{-1} (7.96×10^{-2}) +	3.3021×10^{-1} (5.29×10^{-2}) +	1.0352×10^{0} (3.28×10^{-1})
	132	6	9.9260×10^{-1} (1.88×10^{-1}) +	8.0736×10^{-1} (3.08×10^{-1}) +	7.7376×10^{-1} (7.01×10^{-2}) +	2.3381×10^{0} (5.63×10^{-1})
	156	8	5.8592×10^{0} (1.37×10^{0}) -	2.7670×10^{0} (1.16×10^{0}) +	1.8756×10^{0} (4.91×10^{-1}) +	3.9025×10^{0} (1.20×10^{0})

274	10	1.0327×10^1 (1.28×10^0) -	9.1760×10^0 (2.43×10^0) -	7.3363×10^0 (1.41×10^0) =	6.6987×10^0 (1.35×10^0)
135	15	1.6973×10^1 (1.53×10^0) -	1.9521×10^1 (3.77×10^0) -	1.6151×10^1 (2.64×10^0) -	1.2541×10^1 (1.40×10^0)
+/-/=		2/30/3	6/22/7	6/21/8	

For DTLZ1 and DTLZ3, due to the multi-modal of these functions, it is difficult to get a good convergence solution. However, compared with other algorithms, LEACH-ABF has achieved good results on 6-15 objectives, and it also has the same performance as EFRRR algorithm on 4 objectives, as shown in **Table 2**. The reason is that the choice PBI strategy used to better balance the convergence and distribution of the solution. The PF of DTLZ2 is concave. As can be seen from **Table 2**, the effects of 8 and 15 objectives are slightly worse than NSGA-III, but the effects on 4 and 6 objectives are much better, while the 10 objectives are similar to KnEA. This is because the early stage of the algorithm is biased towards diversity rather than convergence. But the overall performance is better than other algorithms. DTLA4 is biased, and the overall performance of LEACH-ABF and EFRRR is similar, but slightly worse on the 15 objectives. The maximum ranking strategy is adopted by EFRRR effectively increases the selection pressure. The overall performance is superior to NSGAIII and KnEA compared to other algorithms. The PF of DTLZ5 and DTLZ6 is a degenerate curve, which makes it difficult to obtain the convergence and diversity of the solution when solving MaOPs. However, LEACH-ABF overcomes this difficulty and has achieved good results. The main reason is that the ABF strategy plays a major role in improving the convergence and distribution of the algorithm. DTLZ7 is a model of mixed, disconnected and multi-model, which requires very high algorithm design. LEACH-ABF is significantly better than other algorithms on 10, 15 objects, while the performance is degraded at 4, 6, and 8 objectives. And the overall performance is good due to the influence of the selection strategy.

To better understand the distribution of the solution, **Fig. 3** shows the parallel coordinates of the non-dominated fronts obtained by the four algorithms on four objectives for the DTLZ2 test problem. It can be seen that the non-dominated front of the LEACH-ABF algorithm is prospective in terms of convergence and diversity. At the same time, distribution of NSGA-III and KnEA is densely, which cannot well reflect diversity of population. The non-dominated PF of EFRRR has good performance in terms of convergence, but the distribution is slightly worse than the LEACH-ABF algorithm. It can be seen that the solution of LEACH-ABF is at the center of the PF, which can maintain a better diversity. In summary, the algorithm LEACH-ABF is better than other algorithms.
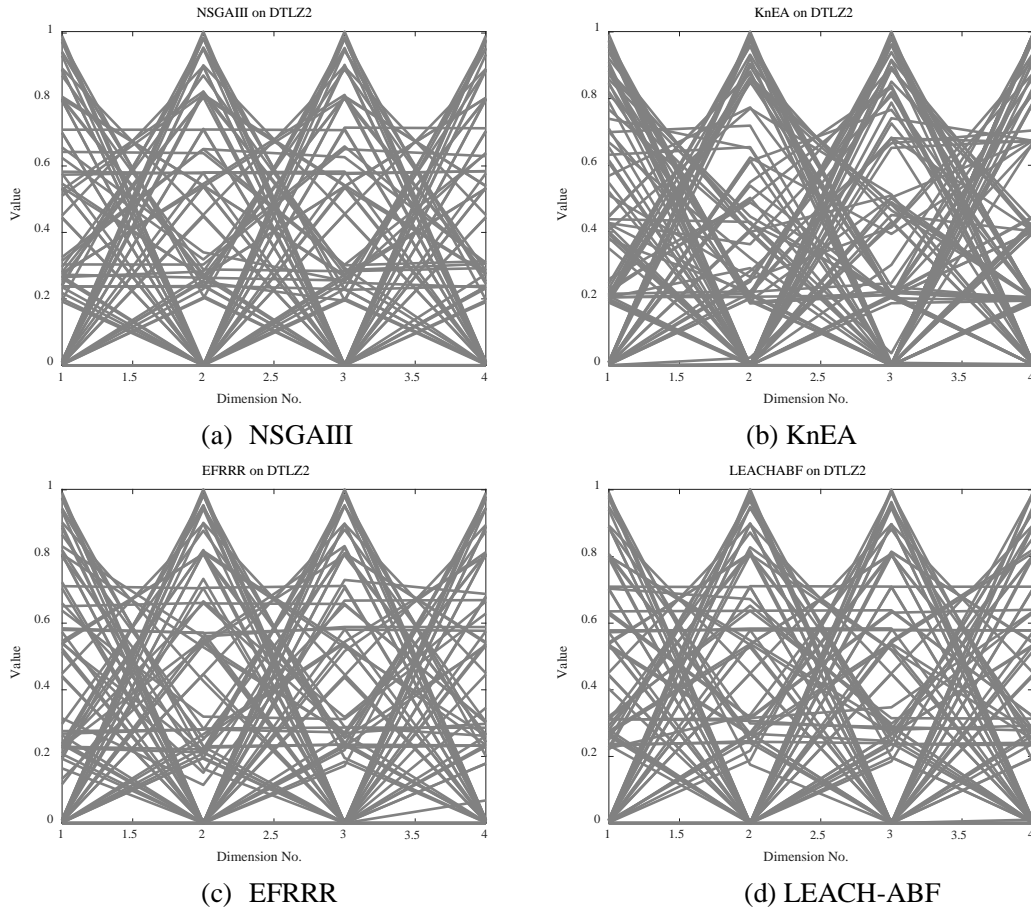
(a) NSGAIII   (b) KnEA

(c) EFRRR   (d) LEACH-ABF

Fig. 3. PF of four algorithms on DTLZ2 with four objectives.
(a) NSGAIII (b) KnEA (c) EFRRR (d) LEACH-ABF

5.2 The performance of LEACH-ABF on wireless sensor network energy balance many-objective optimization model

For the purpose of verifying the effectiveness of the improved algorithm, this section makes a simulation comparison experiment between the improved algorithm LAEACH-ABF and three different algorithms on the wireless sensor energy balance many-objective optimization model. The WSN simulation parameters are set as shown in **Table 3**.

Table 3. Wireless sensor network simulation parameter setting

The parameter type	Value
The area of network	100m*100m
Initial energy	2J
Number of nodes	100
Maximum number of cycles	2000
Transmit and accept unit data energy consumption	50nJ/bit

Signal amplification energy consumption of unit data in free space	10pJ/bit/m2
Signal amplification energy consumption under unit data in multipath attenuation	0.0013pJ/bit/m4
Data fusion energy consumption	5nJ/bit
Frame length	4000bits
Data fusion ratio	0.7
Transmission threshold	87.5m
Base station location	50,50
Node mobility	fixed

Fig. 4 depicts the comparison of lifetime in four different algorithms, expressed in terms of the number of surviving nodes. Starting from the 1300 rounds, it is obvious that the number of surviving nodes of LEACH-ABF is significantly larger than other algorithms, and this situation has been maintained until the 2000 rounds. **Fig. 5** also shows that the residual energy of the four algorithms is almost the same before 1300 rounds. But as the number of rounds grows, the energy consumption of the LEACH-ABF algorithm is smaller than others three algorithms. The detailed data information for the 2000 rounds is given in **Table 4**.

Table 4. Comparison of four algorithms

	NSGAIII	KnEA	EFRRR	LEACHABF
The number of survive nodes	48	49	51	**55**
The residual energy of nodes	28.9534	28.8228	30.7334	**33.5077**
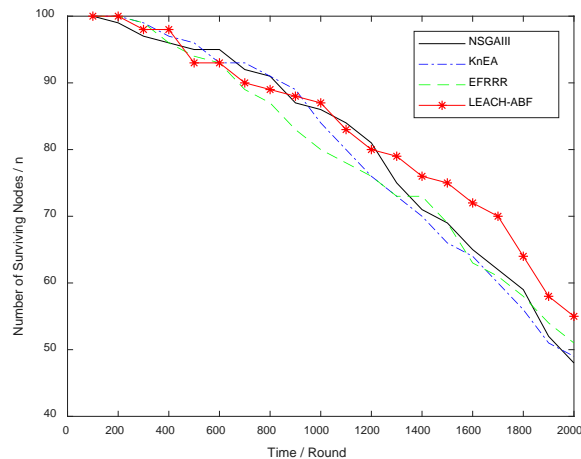
Fig. 4. Comparison of networks lifetime of the algorithm
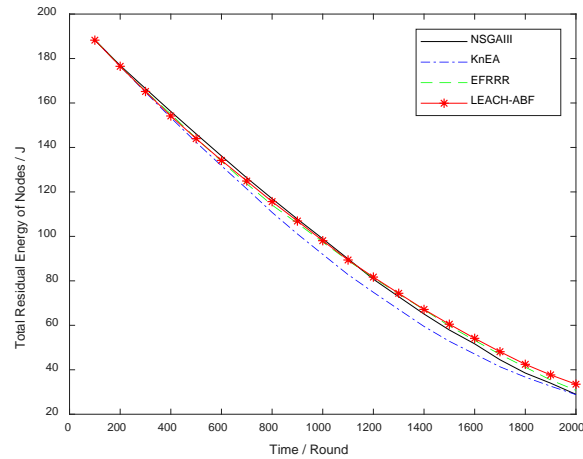
Fig. 5. Comparison of residual energy nodes of the algorithm

In summary, it can be seen that the LEACH-ABF algorithm has the largest number of surviving nodes and the longest lifetime of WSN. The main reason for these results is the rational optimization of the cluster head through the PBI and ABF strategy, which can reduce the total distance transmitted by the entire network node, including not only the communication distance from the cluster head node to the cluster member node, but also the communication distance from the cluster head node to the sink node. For this reason, it can avoid the waste of energy in the communication process and improve the efficiency of energy.

6. Conclusion

As we all know, both the cluster distance and the sink distance will affect the network lifetime. However, the existing work ignores the impact of overall energy consumption of the network and network energy consumption balance on clustering. Therefore, the many-objective energy balance model of cluster head election in LEACH is designed. Taking into account four objectives: the sink node distance, the cluster distance, the overall energy consumption of the network and the network energy consumption balance, which are used to explore that how to choose an instance of a cluster head node. Meanwhile, A new many-objective optimization algorithm LEACH-ABF is proposed to solve the model. ABF adaptively combines the diversity function and convergence function, and uses genetic operations to produce better solutions, so that the optimal solution can be found more efficiently in the solution space. Experiments of DTLZ test suite and comparation test are used to analyze the performance of the algorithm. It shows that LEACH-ABF has better distribution and convergence than other algorithms, which can better balance the energy consumption and extend the lifetime of WSN.

In our future work, we will study and design WSN technology for each specific application in order to make the routing protocol performance superior. Finally, on the basis of the above work, we hope to use the many-objective optimization algorithm to optimize the wireless sensor energy consumption balance problem.

Acknowledgements

References

[1] P. Shunmuga Perumal, V. Rhymend Uthariaraj and V. R. Elgin Christo, "WSN Lifetime Analysis: Intelligent UAV and Arc Selection Algorithm for Energy Conservation in Isolated Wireless Sensor Networks," *KSII Transactions on Internet and Information Systems*, vol. 9, no. 3, pp. 901-920, 2015. Article (CrossRef Link)

[2] K. Daehee, K. Dongwan and A. Sunshin, "Communication Pattern Based Key Establishment Scheme in Heterogeneous Wireless Sensor Networks," *KSII Transactions on Internet and Information Systems*, vol. 10, no. 3, pp. 1249-1272, 2016. Article (CrossRef Link)

[3] Z. Q. Qin, B. X. Lu, M. Zhu, L. Sun and L. Shu, "Optimized Charging in Large-Scale Deployed WSNs with Mobile Charger," *KSII Transactions on Internet and Information Systems*, vol. 10, no. 12, pp. 5307-5327, 2016. Article (CrossRef Link)

[4] T. A. Z. Raza, "A bacterial foraging-based batch scheduling model for distributed systems," *International Journal of Bio-Inspired Computation*, vol. 11, no. 1, pp. 16-26, 2018. Article (CrossRef Link)

[5] M. N. Omidvar, X. Li, Y. Mei and X. Yao, "Cooperative Co-Evolution With Differential Grouping for Large Scale Optimization," *IEEE Transactions on Evolutionary Computation,* vol. 18, no. 3, pp. 378-393, 2014. Article (CrossRef Link)

[6] W. R. Heinzelman, A. P. Chandrakasan and H. Balakrishnan, "Energy-efficient communication protocol for wireless sensor networks," in *Proc. of the 33rd Hawaii International Conference on System Sciences*, January 7, 2000. Article (CrossRef Link)

[7] W. Heinzelman, "Adaptive Protocols for Information Dissemination in Wireless Sensor Networks," in *Proc. of the 5th annual ACM/IEEE international conference on Mobile computing and networking*, pp.174-185, August 15 - 19, 1999. Article (CrossRef Link)

[8] O. Younis and S. Fahmy, "HEED: a hybrid, energy-efficient, distributed clustering approach for ad hoc sensor networks," *IEEE Transactions on Mobile Computing*, vol. 3, no. 4, pp. 366-379, 2004. Article (CrossRef Link)

[9]   W. B. Heinzelman, A. P. Chandrakasan and H. Balakrishnan, "An application-specific protocol architecture for wireless microsensor networks," *IEEE Transactions on Wireless Communication*, vol. 1, no. 4, pp. 660-670, 2002. Article (CrossRef Link)

[10] J. Zhang, H. Yan, Y. Cui, H. Rong and J. P. Wang, "LEACH-EO: A More Energy-Efficient LEACH Protocol for WSN," *Applied Mechanics and Materials*, vol. 644-650, pp. 3108-3111, 2014. Article (CrossRef Link)

[11] B. a. Attea and E. A. Khalil, "A new evolutionary based routing protocol for clustered heterogeneous wireless sensor networks," *Applied Soft Computing Journal*, vol. 12, no. 7, pp. 1950-1957, 2012. Article (CrossRef Link)

[12] Asaduzzaman and H. Y. Kong, "Code Combining Cooperative Diversity in Long-haul Transmission of Cluster based Wireless Sensor Networks," *KSII Transactions on Internet and Information Systems*, vol. 5, no. 7, pp. 1293-1310, 2011. Article (CrossRef Link)

[13] Y. P. Liu, D. W. Gong, J. Sun and Y. C. Jin, "A Many-Objective Evolutionary Algorithm Using A One-by-One Selection Strategy," *IEEE Transactions on Cybernetics*, vol. 47, no. 9, pp. 2689-2702, 2017. Article (CrossRef Link)

[14] J. J. Zhang, F. Xue, X. J. Cai, Z. H. Cui, Y. Chang, W. S. Zhang and W. Z. Li, "Privacy protection based on many-objective optimization algorithm," *Concurrency and Computation Practice and Experience*, vol. 31, no. 20, 2019. Article (CrossRef Link)

[15] Z. H. Cui, J. J. Zhang, Y. C. Wang, Y. Cao, X. J. Cai, W. S. Zhang and J. J. Chen, "A pigeon-inspired optimization algorithm for many-objective optimization problems," *SCIENCE CHINA Information Sciences*, vol. 62, no. 7, p. 070212, 2019. Article (CrossRef Link)

[16] M. Abdel-Baset, Y. Q. Zhou and M. Ismail, "An improved cuckoo search algorithm for integer programming problems," *International Journal of Computing Science and Mathematics*, vol. 9, no. 1, pp. 66-81, 2018. Article (CrossRef Link)

[17] Z. H. Cui, L. Du, P. H. Wang, X. J. Cai and W. S. Zhang, "Malicious code detection based on CNNs and multi-objective algorithm," *Journal of Parallel and Distributed Computing,* vol. 129, pp. 50-58, 2019. Article (CrossRef Link)

[18] K. Deb and H. Jain, "An Evolutionary Many-Objective Optimization Algorithm Using Reference-Point-Based Nondominated Sorting Approach, Part I: Solving Problems With Box Constraints," *IEEE Transactions on Evolutionary Computation*, vol. 18, no. 4, pp. 577-601, 2014. Article (CrossRef Link)

[19] X. J. Bi and C. Wang, "A niche-elimination operation based NSGA-III algorithm for many-objective optimization," *Applied Intelligence*, vol. 48, no. 1, pp. 118-141, 2018. Article (CrossRef Link)

[20] K. Li, K. Deb, Q. Zhang and S. Kwong, "An Evolutionary Many-Objective Optimization Algorithm Based on Dominance and Decomposition," *IEEE Transactions on Evolutionary Computation*, vol. 19, no. 5, pp. 694-716, 2015. Article (CrossRef Link)

[21] Y. Yuan, H. Xu, B. Wang, B. Zhang and X. Yao, "Balancing Convergence and Diversity in Decomposition-Based Many-Objective Optimizers," *IEEE Transactions on Evolutionary Computation*, vol. 20, no. 2, pp. 180-198, 2016. Article (CrossRef Link)

[22] J. Bader and E. Zitzler, "HypE: An Algorithm for Fast Hypervolume-Based Many-Objective Optimization," *Evolutionary Computation*, vol. 19, no. 1, pp. 45-76, 2011. Article (CrossRef Link)

[23] E. Zitzler and S. Künzli, "Indicator-Based Selection in Multiobjective Search," *Lecture Notes in Computer Science*, vol. 3242, pp. 832-842, 2004. Article (CrossRef Link)

[24] X. J. Cai, Y. Niu, S. J. Geng, J. J. Zhang, Z. H. Cui, J. W. Li and J. J. Chen, "An under-sampled software defect prediction method based on hybrid multi-objective cuckoo search," *Concurrency and Computation: Practice and Experience*, 2019. Atricle(CrossRefLink)

[25] X. J. Cai, P. H. Wang, L. Du, Z. H. Cui, W. S. Zhang and J. J. Chen, "Multi-objective 3-Dimensional DV-Hop Localization Algorithm with NSGA-II," *IEEE Sensors Journal*, vol.19, no.21, pp..10003-10015, 2019. Atricle(CrossRefLink)

[26] G. G. Wang, X. J. Cai, Z. H. Cui, G. Y. Min and J. J. Chen, "High Performance Computing for Cyber Physical Social Systems by Using Evolutionary Multi-Objective Optimization Algorithm," *IEEE Transactions on Emerging Topics in Computing*, p.1-1, 2017. Atricle(CrossRefLink)

[27] W. Arloff, K. R. B. Schmitt and L. J. Venstrom, "A parameter estimation method for stiff ordinary differential equations using particle swarm optimisation," *International Journal of Computing Science and Mathematics*, vol. 9, no. 5, pp. 419-432, 2018. Article (CrossRef Link)

[28] X. Zhang, X. T. Li and M. H. Yin, "Hybrid cuckoo search algorithm with covariance matrix adaption evolution strategy for global optimisation problem," *International Journal of Bio-Inspired Computation*, vol. 13, no. 2, pp. 102-110, 2019. Article (CrossRef Link)

[29] X. J. Cai, X. Z. Gao and Y. Xue, "Improved bat algorithm with optimal forage strategy and random disturbance strategy," *International Journal of Bio-inspired Computation*, vol. 8, no. 4, pp. 205-214, 2016. Article (CrossRef Link)

[30] B. P. Zhao, Y. Xue, B. Xu, T. H. Ma and J. F. Liu, "Multi-objective classification based on NSGA-II," *International Journal of Computing Science and Mathematics*, vol. 9, no. 6, pp. 539-546, 2018. Article (CrossRef Link)

[31] H. Kamel, K. Nadjet and D. Habiba, "Multi-objective bat algorithm for mining numerical association rules," *International Journal of Bio-Inspired Computation*, vol. 11, no. 4, pp. 239-248, 2018. Article (CrossRef Link)

[32] Z. H. Cui, Y. Cao, X. J. Cai, J. H. Cai and J. J. Chen, "Optimal LEACH protocol with modified bat algorithm for big data sensing systems in Internet of Things," *Journal of Parallel and Distributed Computing*, vol. 132, pp. 217-229, 2019. Article (CrossRef Link)

[33] X. J. Cai, J. J. Zhang, H. Liang, L. Wang and Q. D. Wu., "An Ensemble Bat Algorithm for Large-scale Optimization," *International Journal of Machine Learning and Cybernetics*, vol.10, no.11, pp.3099-3113, 2019. Article (CrossRef Link)

[34] X. J. Cai, H. Wang, Z. H. Cui, J. H. Cai, Y. Xue and L. Wang, "Bat algorithm with triangle-flipping strategy for numerical optimization," *International Journal of Machine Learning and Cybernetics*, vol. 9, no. 2, pp. 199-215, 2018. Article (CrossRef Link)

[35] N. G. Kumar and D. Chetna, "ESO-LEACH: PSO Based Energy Efficient Clustering in LEACH," *Journal of King Saud University - Computer and Information Sciences*, 2018. Article (CrossRef Link)

[36] X. J. Cai, Y. Q. Sun, Z. H. Cui, W. S. Zhang and J. J. Chen, "Optimal LEACH Protocol with Improved Bat Algorithm in Wireless Sensor Networks," *KSII Transactions on Internet and Information Systems*, vol. 13, no. 5, pp. 2469-2490, 2019. Article (CrossRef Link)

[37] D. B. Jourdan and O. L. D. Weck, "Layout optimization for a wireless sensor network using a multi-objective genetic algorithm," in *Proc. of 59th IEEE Vehicular Technology Conference*, pp. 2466-2470, May 17-19, 2004. Article (CrossRef Link)

[38] K. P. Ferentinos and T. A. Tsiligiridis, "Adaptive design optimization of wireless sensor networks using genetic algorithms," *Computer Networks,* vol. 51, no. 4, pp. 1031-1051, 2007. Article (CrossRef Link)

[39] J. Wang and J. J. Yuan, "A high-efficient multi-deme genetic algorithm with better load-balance," *International Journal of Computing Science and Mathematics*, vol. 9, no. 3, pp. 240-246, 2018. Article (CrossRef Link)

[40] P. H. Wang, J. R. Huang, Z. H. Cui, L. P. Xie and J. J. Chen, "A Gaussian Error Correction Multi-Objective Positioning Model with NSGA-II," *Concurrency and Computation Practice and Experience*, 2019. Article (CrossRef Link)

[41] W. Shi, S. Y. Liu and Z. H. Zhang, "A Lightweight Detection Mechanism against Sybil Attack in Wireless Sensor Network," *KSII Transactions on Internet and Information System*s, vol. 9, no. 9, 2015.

[42] Z. H. Cui, Y. Chang, J. J. Zhang, X. J. Cai and W. S. Zhang, "Improved NSGA-III with selection-and-elimination operator," *Swarm and Evolutionary Computataion*, vol. 49, pp. 23-33, 2019. Article (CrossRef Link)

[43] Q. Z. Lin, S. B. Liu, Q. L. Zhu, C. Y. Tang, R. Z. Song, J. Y. Chen, C. A. C. Coello, K. C. Wong and J. Zhang, "Particle Swarm Optimization With a Balanceable Fitness Estimation for Many-Objective Optimization Problems," *IEEE Transactions on Evolutionary Computation*, vol. 22, no. 1, pp. 32-46, 2018. Article (CrossRef Link)

[44] M. Li, S. Yang and X. Liu, "Shift-Based Density Estimation for Pareto-Based Algorithms in Many-Objective Optimization," *IEEE Transactions on Evolutionary Computation*, vol. 18, no. 3, pp. 348-365, 2014. Article (CrossRef Link)

[45] H. Z. Wu, Y. Q. Zhou and Q. F. Luo, "Hybrid symbiotic organisms search algorithm for solving 0-1 knapsack problem," *International Journal of Bio-Inspired Computation*, vol. 12, no. 1, pp. 25-53, 2018. Article (CrossRef Link)

[46] Q. F. Zhang and L. Hui, "MOEA/D: A Multiobjective Evolutionary Algorithm Based on Decomposition," *IEEE Transactions on Evolutionary Computation*, vol. 11, no. 6, pp. 712-731, 2007. Article (CrossRef Link)

[47] K. Deb, L. Thiele, M. Laumanns and E. Zitzler, "Scalable Test Problems for Evolutionary Multiobjective Optimization," *Evolutionary Multiobjective Optimization: Theoretical Advances and Applications*, pp. 105-145, 2005. Article (CrossRef Link)

Di Wu is currently working toward M.S. degree at computer science and technology, Taiyuan University of Science and Technology, Taiyuan, China. His research interest includes computational intelligence and algorithm optimization.

Shaojin Geng is currently working toward M.S. degree at computer science and technology, Taiyuan University of Science and Technology, Taiyuan, China. His research interest includes computational intelligence and combinatorial optimization.

Xingjuan Cai received her Ph.D. degree in Control Science and Engineering from Tongji University, China, in 2017. She is an Associate Professor with the school of Computer Science and Technology, Taiyuan University of Science and Technology, Taiyuan, China. Her research interest includes bio-inspired computation and application.

Guoyou Zhang received a BS degree in Geological mineral exploration from Jiaozuo Mining Institute, Henan, China, in 1994, MS degree in computer application technology from Taiyuan University of Technology, Shanxi, China, in 2003, and PhD degree in control theory and engineering from Lanzhou University of Science and Technology, Gansu, China, in 2013. Since 2006 he has been a vice professor in the School of Computer Science and Technology, Taiyuan University of Science and Technology, Shanxi, China. His major interests are swarm intelligence and software modelling.

Fei Xue is a Lecturer at School of Information, Beijing Wuzi University. He received the Ph.D. degree in Computer Science and Technology from Beijing University of Technology, China, in 2016. His current research interests are in the areas of swarm intelligence optimization, deep learning and network security.