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Low Energy Adaptive Routing Hierarchy Based on Differential Evolution

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Abstract- In recent years, wireless sensor network (WSN) is a rapidly evolving technological platform with tremendous and novel applications. Many routing protocols have been specially designed for WSN because the sensor nodes are typically battery-power. To prolong the network lifetime, power management and energy-efficient routing techniques become necessary. In large scale wireless sensor networks, hierarchical routing has the advantage of providing scalable and resource efficient solutions. To find an efficient way to decrease energy consumption and improve network lifetime, this paper proposes a centralized routing called Low-Energy Adaptive routing Hierarchy Based on Differential Evolution (LEACH-DE). Simulation results show that the proposed routing protocol outperforms other well known protocols including LEACH and LEACH-C in the aspects of reducing overall energy consumption and improving network lifetime.

Index terms*:* Routing Algorithm, Differential Evolution, Cluster Head, LEACH-DE.

I. INTRODUCTION

Recently researches on wireless sensor network (WSN) have rapidly grown and new techniques have been developed for efficient transmission. Typically, a WSN consists of hundreds or thousands of low cost sensor nodes scattered among danger environments and difficult-to-reach terrains and networked together for collaboratively gathering data from an area of interest [1]. Each sensor node always has an embedded processor, a wireless module, a non replaceable energy and some on-board sensors. Once deployed, sensor node has a limited power supply since it only rely on batteries so that sensor node may fail as a result of energy depletion, communication link errors, and so on [2]. At the same time, where many applications in WSN require many-to-one traffic pattern, multihop forwarding may lead to energy imbalance because all the traffic must be routed through the nodes near the data sink, thus creating a hot spot around the data sink. Nodes in hot spot are required to forward high amount of data and always die at a very early stage. Therefore, energy-efficient routing algorithms, protocols and deployment strategies play key roles in minimizing transmission energy and prolonging network lifetime.

According to the network structure, routing algorithm in WSN can be divided into flat-based routing algorithm, hierarchical-based routing algorithm. Some flat routing algorithm including SPIN (Sensor Protocols for Information via Negotiation), DD (Directed Diffusion), and MCFA (Minimum Cost Forwarding Algorithm) are proposed in early years [3, 4, 5, 6]. Hierarchical routing is an efficient way to lower energy consumption within a cluster and to decrease the number of messages transmitted to the sink node by performing data aggregation. In hierarchical networks, higher energy nodes can be used to process and send the information while low energy nodes can be used to perform the sensing task [7, 8]. Hierarchical routing is typically separated into two phases that one phase is used for selecting cluster heads and the other phase is used for routing and transferring actual data. By clustering, nodes are organized into small groups called clusters. Each cluster has a cluster head (CH) and some non cluster head (non CH) nodes. Compared with flat routing, clustering protocol can provide obvious superiority with respect to energy conservation by facilitating localized control and reducing the volume of inter-node communication [9]. Some of routing protocols in this group are: LEACH [10], PEGASIS, TEEN and APTEEN. LEACH [11] is one of the most studied and referred protocols, which is considered as the ground work for other hierarchical routing.

The paper proposes another clustering-based routing protocol called LEACH based on differential evolution (LEACH-DE), which utilizes differential evolution algorithm to find cluster heads and set up clusters. The motivation behind the LEACH-DE is that selecting the most appropriate CH for a group of sensor nodes by minimizing the distance between CHs and non CH nodes. The rest of the paper is organized as follows. In the next section, the classical hierarchical routing protocols are overviewed with detailed discussions. Section 3 exhibits the structure of LEACH-DE and network model, respectively. In section 4, we evaluate the performance of LEACH-DE and compare the performance of LEACH-DE with that of other hierarchical routing algorithms. Finally, section 5 concludes the paper and highlights some future work directions.

II. RELATED WORK

As previously mentioned, cluster-based routing protocol is to efficiently maintain the energy consumption of sensor nodes by selecting appropriate cluster heads (CHs) and by performing data aggregation in order to decrease the number of transmitted messages to the sink. Among the hierarchical routing protocols in wireless sensor networks, LEACH [11, 12] is a well-known routing protocol, which is used as the ground work for several researches.

2.1 LEACH

In LEACH, time is partitioned into fixed intervals with equal length, which is called topology update interval or round. Each round is generally separated into the setup phase and the steady state phase. During the setup phase, each node decides whither or not to become a CH for the current round based on a predetermined fraction of nodes and the threshold value, T(s). The threshold value is calculated by Eq. (1).

$$T(s) = \begin{cases} \dfrac{p}{1 - p(r \cdot \mathrm{mod}(1/p))} & if \quad s \in G \\ 0 & if \quad s \notin G \end{cases} \tag{1}$$

Where $p = k/N$ is the percentage of cluster head accounted for all nodes, r is the number of election rounds, $r \cdot \mathrm{mod}(1/p)$ refers to the number of nodes elected in the previous r-1 round of cycle, and G is a set of non elected nodes in the previous r-1 round. In steady-state phase, nodes can begin sensing and transmitting data to the cluster heads during their allocated transmission slot. To reduce energy dissipation, the radio of non cluster head node is immediately turned off after transmitting data. Once the cluster head receivers all the data, it performs data aggregation before sending data to the base station (BS).

2.2 LEACH-C

In [12, 13], an extension to LEACH, LEACH-C is proposed. In order to ensure energy load is evenly distributed among all the nodes, the sink node in LEACH-C finds clusters using the simulated annealing to solve the NP-hard problem of finding k optimal clusters. During the setup phase, each sensor node transmits information about its location and remaining energy to the BS. The BS computes the average node energy, and the nodes whose energy level is above this average value may be selected as CH in the current round. This algorithm uses simulated annealing algorithm for selecting CH, which can minimize the total sum of distances between CH nodes and non CH nodes in order to decrease the total power consumption of the WSN. The overall performance of LEACH-C is better than LEACH since LEACH-DE moves duty of cluster formation to the base station (BS), predetermines the optimal number of cluster, selects the appropriate nodes as CH.

2.3 TL-LEACH

As a single-hop routing algorithm for WSN, the CH collects and aggregates data from nodes and transmits the information to BS directly in LEACH. According to the radio energy dissipation model, both the free space (d^2 power loss) channel models and the multipath fading (d^4 power loss) channel models are used. Which channel model is used depends on the distance between the transmitter and receiver. To transmit a l-bit message for a distance d, the radio expends the amount of energy is described by Eq. (2).

$$E(l,d) = \begin{cases} lE_{elec} + l * \varepsilon_{fs} * d^2 & d < d_0 \\ lE_{elec} + l * \varepsilon_{mp} * d^4 & d \geq d_0 \end{cases} \tag{2}$$

The electronics energy E_{elec} depends on factors such as the digital coding, modulation, filtering, and spreading of the signal, whereas the amplifier energy ε_{fs} or ε_{mp} depends on the distance to the receiver and the acceptable bit-error rate. The short distance is defined as $d_0 = \sqrt{\varepsilon_{fs} / \varepsilon_{mp}}$. In LEACH, each CH directly communicates with sink no matter the distance between CH and BS is far or near. CH will consume lots of energy for transmit data if the distance is greater the threshold d_0. Losci et al. [13] proposed a two-level hierarchy for LEACH (TL-LEACH) which uses one of CH that lie between the CH and the BS as a relay station. This algorithm utilizes two levels of cluster heads (primary and secondary). The primary cluster head in each cluster communicates with their secondaries, and the corresponding secondaries communicate with the sensor nodes in their sub-cluster. The algorithm can effectively prolong the lifetime of battery-powered sensor nodes because transmit distance is reduced. LEACH-type protocols have received significant developed recently, but some shortcoming of those protocols should be attention.

As mentioned above, LEACH and TL-LEACH [14] are completely distributed and requires no any global knowledge of the network. LEACH-C is an improved scheme of LEACH in which a centralized algorithm at BS makes cluster formation, which needs GPS or other location-tracking method in order to gain the position of sensor nodes. The core algorithm of LEACH-C is simulated annealing (SA) which is a traditional generic probabilistic metaheuristic for the global optimization with slowly convergence [15]. SA is a randomized gradient descent algorithm, which permits uphill moves with some probability so that it can escape local minima. But SA is not universal and its performance is dependable on some requirements which make SA converge very slowly in most the global optimization, these requirements include that the initial temperature is high enough, the temperature is cooled slowly enough, etc. These protocols do not guarantee that appropriate nodes are select as CHs [16].

2.4 Swarm intelligence

Swarm intelligence (SI) [17] is developed from the imitations which are learned from the social behaviors of insects and animals, for example: Differential Evolution (DE) [18], ant colony optimization (ACO) [19], particle swarm optimization (PSO) [20], and the like. SI has found practical applications in areas such as intelligent control, robotics, and wireless sensor network. Researchers have successfully used SI techniques to address many challenges in WSN. Among these SI techniques, DE is successfully applied to a remarkable number of NP-hard problems because of search through vast spaces of possible solutions [21]. Clustering a network to minimize the total energy dissipation is an NP-hard problem. For the total number of sensor nodes in WSN is N, a sensor node is either elected as CH or non CH in each solution so that there are $2^N - 1$ different combination of solutions for the WSN [11]. So DE can been applied for solving NP-hard problem. Storn and Price(1995) firstly proposed the differential evolution (DE) which has become one of the most frequently used evolutionary algorithms for solving the global optimization problems [22]. Compared with most evolutionary algorithms, DE is based on a mutation operator, which adds an amount obtained by the different of two randomly chosen individuals of the current population. The algorithm of DE is shown as follow:

1. generate an initial population $P = \{X_1, X_2, ..., X_N\}, X_i \in D$
2. repeat
3. For i:=1 to N do
4. Generate a new trial vector Y_i
5. if $f(Y_i) < f(X_i)$, then y replace X_i
6. end if
7. generate new population P'
8. end for
9. until the termination condition is achieved

The next generation $X_i(t+1)$ is determined by the following three operations: mutation, crossover and selection.

- Mutation

Mutation strategies were previously proposed in [23], the most popular mutation strategy called DE/rand/1/bin. Mutate individual of DE/rand/1/bin is generated according to the following equation:

$$Y_i(t) = X_{i_1}(t) + f_m[X_{i_2}(t) - X_{i_3}(t)]$$

$i = 1,2,\cdots,N$ is the individual's index of population; $X_{i_1}, X_{i_2}, X_{i_3}$ are randomly chosen vectors from the set $\{X_{i_1},\cdots,X_{N_p}\}$; N_p is the population size; the mutation factor f_m is a parameter in $[0,1]$, which controls the amplification of the difference from two individuals so as to avoid search stagnation [24]. The other frequently referenced mutation strategies are listed below:

(1) "DE/Best/1": $Y_i(t) = X_{best}(t) + f_m[X_{i_1}(t) - X_{i_2}(t)]$

(2) “DE/RandToBest/1”: $Y_i(t) = X_i(t) + f_m[X_{best}(t) - X_i(t)] + f_{m1}[X_{i_1}(t) - X_{i_2}(t)]$

(3) “DE/Best/2”: $Y_i(t) = X_{best}(t) + f_m[X_{i_1}(t) - X_{i_2}(t)] + f_{m1}[X_{i_3}(t) - X_{i_4}(t)]$

(4) “DE/Rand/2”: $Y_i(t) = X_{i_1}(t) + f_m[X_{i_2}(t) - X_{i_3}(t)] + f_{m1}[X_{i_4}(t) - X_{i_5}(t)]$

(5) “DE/RandToBest/2”:

$$Y_i(t) = X_i(t) + f_m[X_{best}(t) - X_i(t)] + f_{m1}[X_{i_1}(t) - X_{i_2}(t)] + f_{m2}[X_{i_3}(t) - X_{i_4}(t)]$$

- Crossover

Crossover operations are applied to increase the potential diversity to the population which use binomial crossover scheme. The binomial crossover scheme constructs the trial vector by taking , in a random manner, elements either from the mutant vector $X_i(t)$ or from the current element $Y_i(t)$, as is described in Eq.(3).

$$\widehat{Y}_i^j(t) = \begin{cases} Y_i^j(t) & if \quad rand(0,1) <= CR \quad or \quad j = I_i \\ X_i^j(t) & otherwise \end{cases} \tag{3}$$

I_i is a randomly selected index from $\{1,2,\cdots n\}$ which ensures that at least one component is take from the mutant vector $Y_i(t)$ .The parameter CR (crossover rate) is a user-specified constant within the range [0,1] which controls the number of components inherited from the mutant vector and influences the convergence speed.

- Selection

When all N trial points $\widehat{Y}_i(t)$ have been generated, selection operation is applied. We must decide which individual between $X_i(t)$ and $\widehat{Y}_i(t)$ should survive in the next generation $X_i(t+1)$, the selection operator is described as follows:

$$X_i(t+1) = \begin{cases} \widehat{Y}_i(t) & if \quad f(\widehat{Y}_i(t)) > f(X_i(t)) \\ X_i(t) & otherwise \end{cases}$$

In addition the DE dynamically tracks current searches with its unique memory capability to adjust its search strategy. DE has comparatively strong global convergence capability and robustness and no need with the help from information about the characteristics of problems [25].

III. THE PROPOSED ALGORITHM LEACH-DE

To increase the lifetime of WSN, this paper proposed an energy efficient routing algorithm, this is, LEACH based on DE algorithm (LEACH-DE). LEACH-DE is a specially designed routing algorithm for WSN with the sink being an essential component with complex computational abilities, thus the other nodes being very simple and cost effective. LEACH-DE works in rounds as LEACH and each round consists of two main phases, the setup phase and the steady state phase. During the setup phase, the selection of the cluster-head follows the similar criteria as LEACH, but the algorithm of selection cluster-head in LEACH-DE is differential evolution algorithm. The setup phase is subdivided into selection of cluster-head phase and formation of cluster phase. The flowcharts of selecting cluster-head phase and formatting of cluster phase are respectively shown in Figure 1(a) and Figure 1(b).

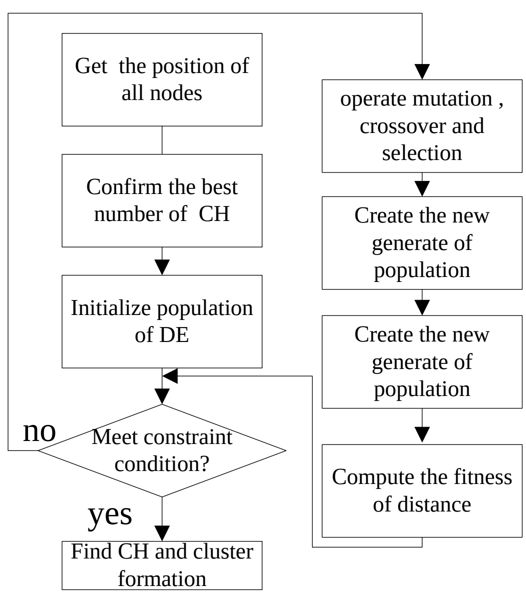


Figure 1(a). Selection of cluster-head phase

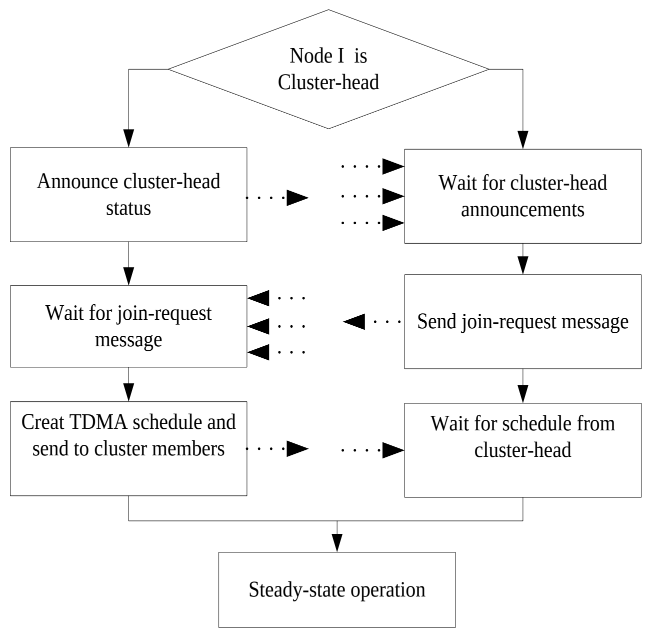


Figure 1(b). Formation of clustering phase.

In this paper, the simulation assumed that there are 100 sensor nodes and one sink which are randomly dispersed in a two-dimensional square field and sensor network has the following properties:

- There are only one sink in the network, which is static and no energy constraints.
- Sensor nodes are non-rechargeable, have equal initial energy and always have data to send.
- Packets loss due to factors other than the energy exhausting of node not exist or is ignorable
- Nodes are aware of their location.

- Communication from each node can be used by the radio energy dissipation model which presented in Eq.(2).
- Each node can directly communicate with the sink.

The WSN in the paper can be modeled as an undirected graph $G=(V,E)$ where, V is the node set and E is an edge set. There are the total of N sensor nodes are initially distributed randomly in a two-dimensional field A, S is a set of N and $k \le N$ a positive integer. A k-clustering of S into k subsets $S_1, S_2 \cdots S_k$.Each S_i is called a cluster which has one CH and some non CH nodes. Non CH node in the cluster sends data to its CH only. The goal of the clustering algorithm attempts to minimize the amount of energy for the non cluster head nodes to transmit their data to the cluster head, by minimize the total sum of distance between all the non CH nodes and the closest cluster head. The clustering problem can be considered as k-mean problem which is NP-Hard. So in the cluster S_i, the number of the non CH nodes is N and the distance between CH and the non CH node j can be computed as given below.

$$CHdis(S_i, j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{4}$$

Where, (x_i, y_i) and (x_j, y_j) represent the position of the CH and the node j. According of the goal of the clustering problem, we should find a set $S \in V$, with $S = K$ so as to

$$\min \ \ \cos t(S,V) = \min \sum_{i=1}^{K} \sum_{j=1}^{N} CHdis(S_i, j) \tag{5}$$

$$\text{Subject to : } 0 \le x_i, y_i \le 100$$

The objective function can be solved by different heuristics algorithms. For such routing protocols, the number of clusters within the network is highly affecting to the network lifetime and the energy consumption. The optimal number of clusters is very important. Numerical simulate tests showed that if the number of clusters are not equal to an optimal number, the total consumed energy of the sensor network per round is increased significantly. In [12], k_{opt} which is the optimum number of CHs within the network can be calculated by Eq. (6).

$$k_{opt} = \frac{\sqrt{N}}{\sqrt{2\pi}} \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} . \frac{M}{d_{toBS}^2} \tag{6}$$

Where d_{toBS} is the distance from the CH to the BS.

The pseudo-code of the LEACH-DE algorithm is given below:

Definitions:

D: Dimensions of problem, D=2 in the paper

NP: population size

CR: crossover rate

F: scale factor

MNG: maximum number of generations which is a termination criterion.

new_index(i,:): The vector index with the lowest cost

Cost(S,V): The distance of CHs and non CHs

MNG: Maximum number of generations specified

FM_popold: Initial population

FM_ui: New population

F_weigh: The weighted vector difference

Maxbound: The upper bound value, Maxbound=100

Minbound: The lower bound value, Minbound=0

find_min_dist: Distance calculation function

step 1: Generate one sink and 100 homogeneous sensor nodes, which are shown in **Fig.2**.

step 2: Initialize the values of D and key parameters (NP, CR, F and MNG).

step 3: Randomly generate population. The population consists of NP competitions, and each competition has k_{opt} CH nodes in the study.

For i=1 : NP

{For j=1 to k_{opt}

InitCutou(i,j)=random number

{ x1(i,j)=x(1, InitCutou(i,j));

y1(i,j)=y(1,InitCutou(i,j)) }

Generate population: FM_popold=[x1,y1]}

step 4: Evaluate the Cost(S,V) of each vector according to Eq. (5), find out CHs.

For i=1 to NP

{Cost(S,V)=find_min_dist(x1(i,:),y1(i,:),size1,x2,y2,size2);

Find out new_index(i,:)}

Where x1(i,:), y1(i,:), size1 are the x- , y- coordinate and the number of CH respectively, and x2,y2,size2 are the x-, y- coordinate and the number of non CH respectively.

step 5: Perform mutation, crossover, selection and evaluation of the objective function Cost(S,V).

While (gen< MNG)

{ for i=1 to NP

● Perform mutation for each target vector.

When the mutation strategy is DE/rand/1,

FM_ui = FM_pm3 + F_weight(FM_pm1 - FM_pm2);* (The other mutation strategies can be seen in section 2)

● Perform Binomial crossover.

If ($rand(0,1) \leq CR$ *or* $j = I_i$)

*FM_ui = FM_popold.*FM_mpo + FM_ui.*FM_mui;*

● Check whether new vector are within the bounds. If not, the new vector must be restricted within the bounds.

if (FM_ui(k,j) > FVr_maxbound)

FM_ui(k,j) = maxbound + rand(origin(k,j) - maxbound);*

if (FM_ui(k,j) < FVr_minbound)

FM_ui(k,j) = minbound + rand(origin(k,j) - minbound);}*

● Find out new CHs.

Through the above process, the five CHs calculated may be not sensor nodes. The "new" CHs can be found out according to the minimal distance.

Cost(S,V)=*find_min_dist(x1new(i,:),y1new(i,:),size1,x2,y2,size2)*

Find out new_index(i,:)

- Perform selection.

    For i=1 to NP

    { if (costnew(i) <cost(i))

    new $X_i(t)=\hat{Y}_i(t)$;

    otherwise new $X_i(t)=X_i(t)$}

- Print the results and continue.

    Print the results;

    If (gen< MNG)

    gen=gen+1

    Jump to **step 5.**

IV. PERFORMANCE EVALUATION

4.1 Comparison between different strategies of DE

The clustering of WSN is optimization problem in the sense that energy consumption is distributed over all sensor nodes and the energy consumption of whole network is minimal. To evaluate the performance of LEACH-DE, simulation experiments were tested with various experimental scenarios which were simulated in Matlab. The experiments were carried out in two major phases. In the first phase, the paper evaluates the different strategies of DE and determines the most appropriate parameters and strategy. In the second phase, the paper compares the performance of LEACH-DE with that of LEACH and LEACH-C in terms of the convergence value and total remain energy in the network.

In the study, five strategies of DE are used to solve the Eq. (5). They are DE/Best/1, DE/RandToBest/1, DE/Best/2, DE/Rand/2 and DE/RandToBest/2 which are given in section 2. The result of the strategies are studied to find the most strategy and the most parameters for minimize the total sum of distance between all the non CH and CH according to the Eq. (5). In the simulation experiments, we set the parameters of WSN as [7], that is, N=100, M=100m, 75m< d_{toBS} <185m, $\varepsilon_{fs}=10pJ$, $\varepsilon_{mp}=0.0013pJ$, and k_{opt} =5.

The simulated WSN consists of one sink which located at the origin of coordinate system and 100 homogeneous sensor nodes randomly deployed within the sensing field from (0,0) to (100,100), which be shown in Figure 2.

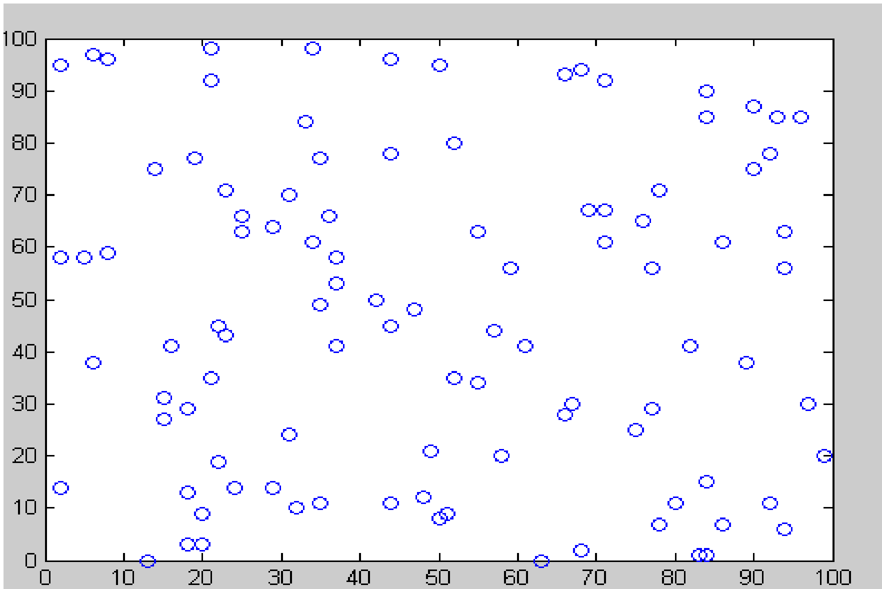


Figure 2. Sensor nodes deployed in WSN

Figure 3 shows the example of dynamic cluster formation. All nodes marked with a given symbol belong to the same cluster, and CHs are marked with a circle.

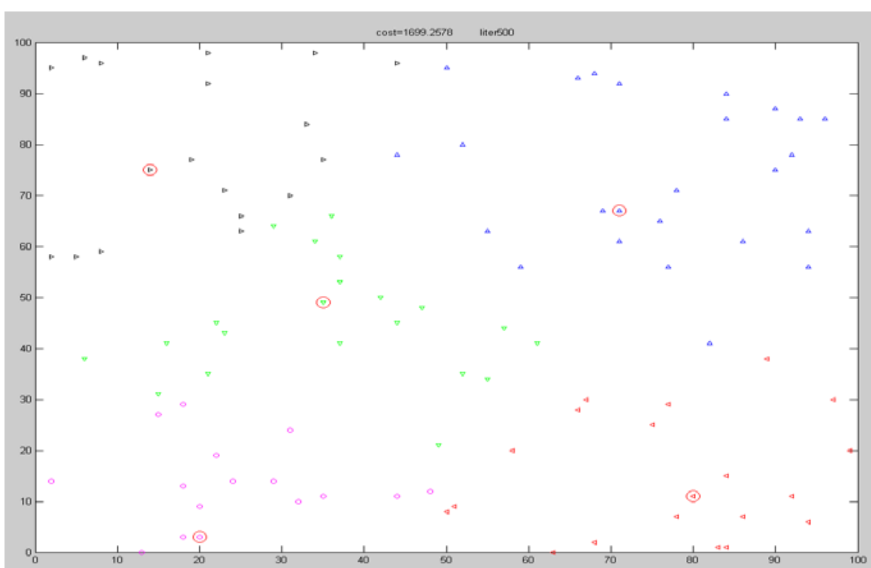


Figure 3. Example of dynamic cluster formation

In every generation, five nodes are selected as CHs which can be conceded as a seed in order to minimize $\cos t(S,V)$. Normally, NP (population size) should be about 5~10 times the number of parameters in a vector, in the study, NP=10. Maximum number of generations (MNG) is the number of iterations that the algorithm will run. For easy problems, one may start with 100 generations. Then, if necessary, the value can get increased until the algorithm can not improve result. In the paper, MNG is 1000.

In order to validating the effectiveness of the LEACH-DE and determined the appropriate parameter, 500 independent runs were performed in the paper. The performance of DE depends on key parameters, namely, mutation strategy, CR, F, and NP. By choosing the key parameters (mutation strategy, NP, CR, and F) appropriately, the problem of premature convergence can be avoided to a large extent. The paper applies the simulation with the following parameter settings: NP=10, MNG =1000. CR is varied from 0.1 to 1 at step of 0.1 and F is varied from 0.1 to 1 at step of 0.1, which can be seen in the Table 1.

Table 1 Parameter setting of LEACH-DE

Parameter / Algorithm	NP	MNG	CR	F	Strategy
LEACH-DE	10	1000	(0.1~1) step=0.1	(0.1~1) step=0.1	1~5

Now, in order to study the effect of F and CR on various strategies, the criterion considered is “converge to the minimum value”. In LEACH-DE, f_m (scale factor) influences the diversity of the set of mutant vectors and CR（crossover rate） controls the fraction of parameter values copied from the mutant vector. In the study, the best combination of CR and f_m are chosen by trial and error. CR was varied from 0.1 to 1 at step of 0.1, f_m was varied from 0.1 to 1 at step of 0.1， which leading to 100 combinations of CR and f_m for the DE algorithm.

When the LEACH-DE algorithm is executed with five strategies for all the above combinations, the results of numerical simulation show that the globe minimum value for Eq. (5) is 1635.5 which is likely to converge to the true global optimum. Every strategy can converge to the minimum value（1635.5） but the numbers of converging the minimum is different. DE/Rand/2 and DE/RandToBest/2 can reach the globe minimum more than 20 times and have the lower average convergence value which means the two strategies have more superior performance than other strategies. Table 1 shows the final convergence situation for different strategies.

Table 2 Final convergence situation for different strategies

Convergence value Strategy	**Average final convergence value**	**Numbers of converging to minimum**
DE/Best/1 (Strategy 1)	1685.8	8
DE/RandToBest/1 (Strategy 2)	1690	3
DE/Best/2 (Strategy 3)	1732.4	5
DE/Rand/2 (Strategy 4)	1669	20
DE/RandToBest/2 (Strategy 5)	1646.4	21

The results in the Table 2 record the final convergence situation for different strategies. From the Table 2, it is observed that if for a given certain condition, by using DE/best/1… (Strategy numbers 1 to 5) the global minimum can be achieved in a certain generations. Results in the Table 2 clearly illustrate that the strategy 4 and strategy 5 are significantly better than the other strategies in that the strategy 4 and strategy 5 can converge to minimum value above twenty times against other strategies can not.

Once good strategies are chosen, the next step is to study the effect of the key parameters of DE to find the best combinations of F and CR for good strategies. So the study selects DE/Rand/2 and DE/RandToBest/2 (strategy 4 and strategy 5) as the core strategies of LEACH-DE. Figure 4 shows the situation of final convergence value of strategy 4 and strategy 5 at the different combinations of F and CR.

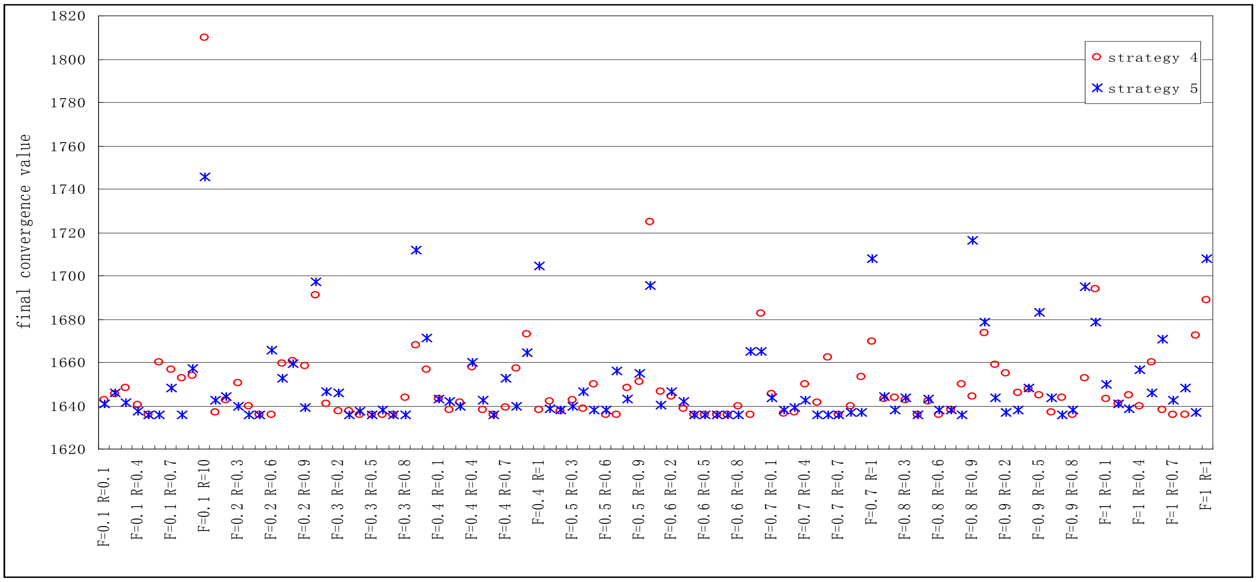


Figure 4. The final convergence value of strategy 4 and strategy 5 at the different combinations of F and CR

In order to study the effect of F and CR, simulation tests using the following parameters: NP=10, CR=0.6, the maximum generation is 1000, and f varies from 0 to 10 at step of 0.1, each experiments repeats 20 times independently. Simulation results show that all the best average objective value in Eq. (5) decreases quickly when F increases. The algorithm can be easily trapped in local minimum. When F is too small, objection function value can avoid premature but weakens the exploitation ability of optimization. In the study, LEACH-DE has the better performance when F equal to 0.6. In the next step is to study the effect of the CR. Analogous to the above experiments, the simulation tests carry out while CR varies from 0 to 10 at step of 0.1. When CR increases, it found clearly the speed of convergence become fast but the best solution almost cannot be obtained. However, when CR become small, the speed of convergence become slowly also.

Numerical results show that F is 0.6 and CR varies from 0.3 to 0.6 at step of 0.1, the convergence value can be equal or close to the global minimum. To compare the convergence value of different strategies, the final convergence value for each strategy is listed in Figure 5.

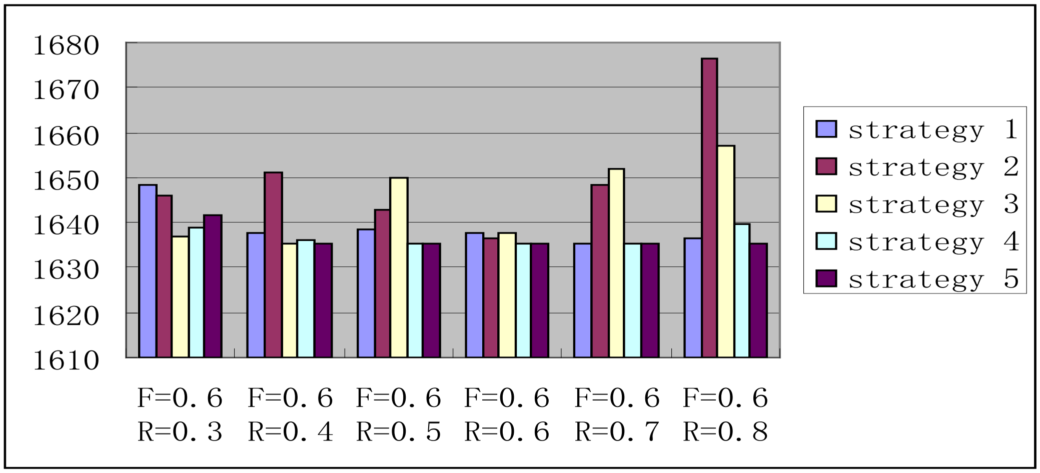
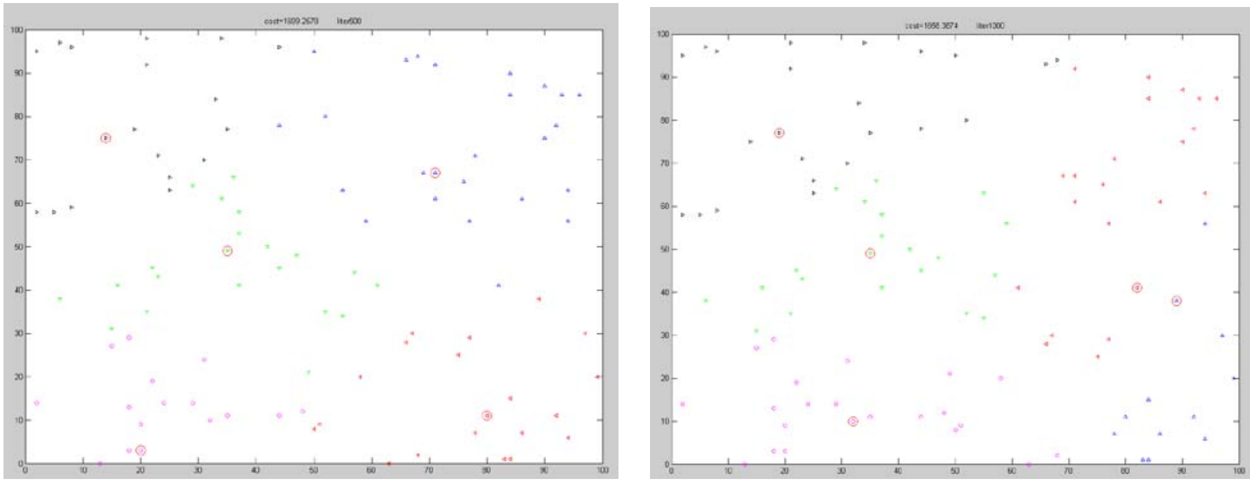


Figure 5. The final convergence value for each strategy at F is 0.6 and CR varies

When F =0.6 and CR =0.6, strategy 4 and strategy 5 can get excellent converge value. Compare the situation of convergence from numerical test, it can draw a conclusion that the LEACH-DE can be achieve good result when F =0.6 and CR =0.6.

In order to explain the process of simulation, the following Figures were given. Under the prefect parameters, this is F =0.6, CR =0.6 and the number of strategy is five, simulation test was carry out. Figure 2 shows the position of 100 sensor nodes in the monitor area and the CHS which is decided by the LEACH–DE (surrounded by a circle) at the initialization iteration.

Figure 6(a~b) shows an example of the clusters formed of LEACH-DE（F=0.6 and CR=0.6）at 100 iteration, 300 iteration respectively.



(a) (b)

Figure 6. Dynamic cluster formation at different iteration

Figure 7 shows the convergence value graphs for each generation. As it is clear from Figure7 the curvatures are estimated pretty well and show how LEACH-DE can be efficient.

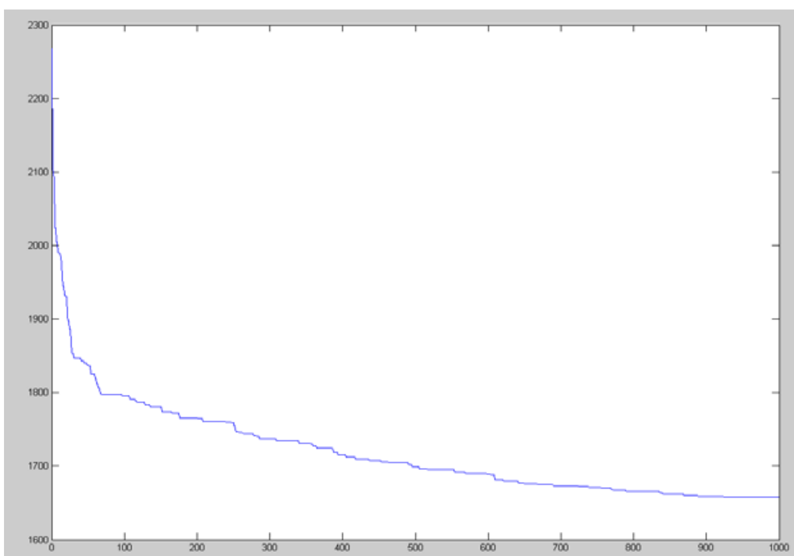


Figure 7. The convergence value graphs

4.2. Comparison LEACH-DE with other routing algorithms

In this section, the paper evaluates the performance of LEACH-DE protocol. Since LEACH-DE is a hierarchal routing protocol, we compare it with other hierarchal routing protocol such as LEACH and LEACH-C. Two performance criteria are selected to evaluate the performance of three algorithms. The criteria are also described as follows: The convergence value and residual Energy.

- The convergence value: the total distance in whole WSN between CHS and non CH nodes. The value can be computed by Eq. (5).
- Residual Energy: equal to total initial energy minus energy consumption in the first *n* iterations, transmit model can be seen in Eq. (2).

(1) Comparison of the convergence value

For comparing performance of LEACH-DE, LEACH and LEACH-C, three algorithms are conducted for independent runs. In order to make direct comparisons possible, the LEACH-C and LEACH have been applied to solve the routing problem. Each algorithm has its own parameters that affect its performance and the quality of solution. Large numbers of simulation test are conducted by varying different parameters for each routing algorithm in order to obtain the best result. The core algorithm of LEACH-C is SA (simulate annealing algorithm) algorithm. SA's major advantage over other methods is an ability to avoid becoming trapped at local minima. The algorithm employs a random search, which not only can accepts changes that decrease objective function(make it better), but also accept some changes increase it(make it worse) with a probability *P*.

$$P = e^{-\Delta / T} \tag{7}$$

Where Δ is the increase in objective function, this is cost(iteration +1) minus cost(iteration) in the study. T which is the value of the temperature and decreases in each iteration can be computed by 1000 * exp(-iteration / 20). For comparing fairly with LEACH-DE, the LEACH-C selects 10 solutions in each iteration to find the better convergence value. In the way, the LEACH-C can expand optimization search range and reduce optimization time.

As demonstrated by the results shown in Figure 8, the LEACH-C can converge to the acceptable results but difficult to converge global minimum. At the beginning stage of LEACH-C, convergence graph is apparently fluctuant in that the SA can accept some worse results which mean that the solution with a large objective value than the current objective solution can be survived to the next generation. As number of iteration increase, the objective function value decreases smoothly, but convergence speed is comparatively slow and at last the value is no change after 800 generations. Figure 8 shows the convergence graph of LEACH-C which converge to about 2200.

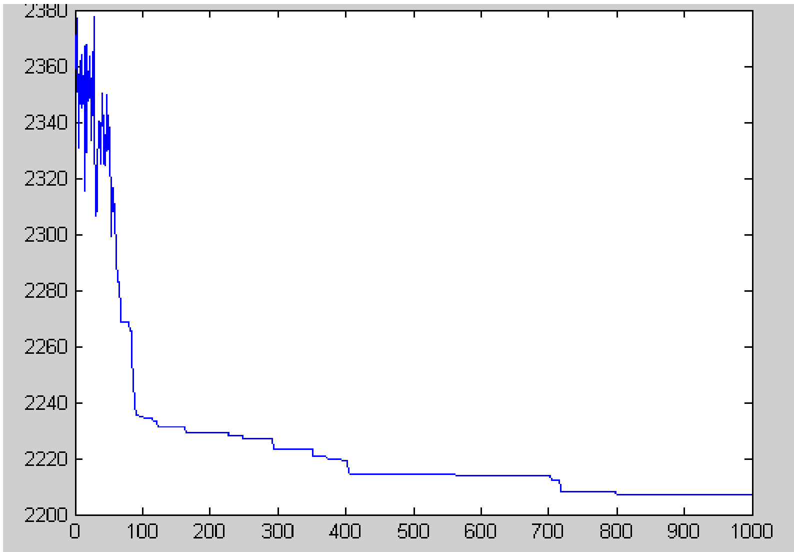


Figure 8. The convergence graph of LEACH-C

The number of CHS of LEACH-DE and LEACH-C is determined in Eq. (6) which is appropriate to the WSN. The algorithms choose five sensor nodes as cluster head in each iteration. But in LEACH, nodes organize themselves into clusters using a distributed algorithm periodically, this is, sensor nodes elect themselves to be CHS with probability $P_i(t)$ in the literatrue [12]. So the number of CHS in LEACH is uncertain, which lead to graph of the distance between CHS and other nodes can not converge. The convergence graph of LEACH is shown in Figure 9.

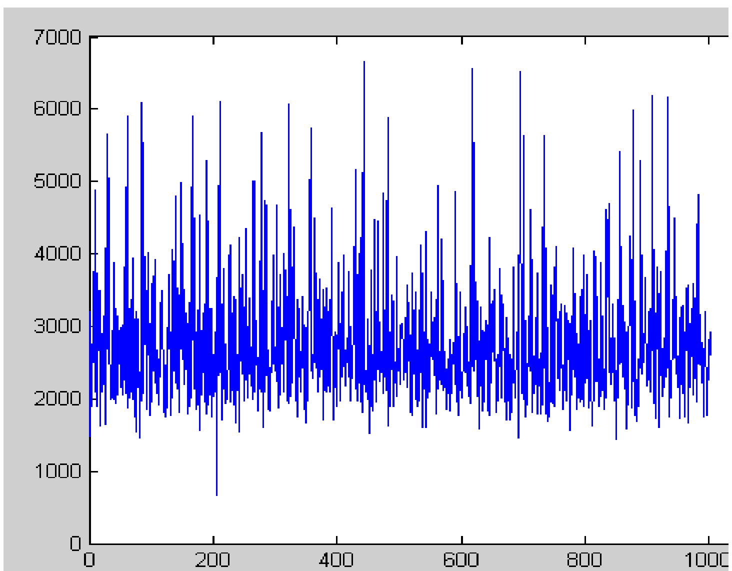


Figure 9. The convergence graph of LEACH

From the view of "convergence" to consider, the LEACH-DE and LEACH-C are better performance over LEACH for decrease the total communication distance which is direction relationship with the energy consumption. In order to investigate the ability of converge of three algorithm, a set of experiments has been performed with parameters unchanged, the results are presented in Table 3.

Table 3 Comparison of LEACH, LEACH-C and LEACH-DE in Convergence value

Algorithm	**Average final convergence value**	**After 100 iteration**	**After 200 iteration**	**After 1000 iteration**
LEACH	2765.8	2765.3	2767.3	2769.2
LEACH-C	2270.9	2264.6	2261.7	2260.1
LEACH-DE	1694	1676.7	1665.4	1657.3

The performance of LEACH, LEACH-C and LEACH-DE are compared in Table 3. From the Table 3, it can be seen that LEACH-C can provide better result and at the same time LEACH significantly worse than LEACH-C and LEACH-DE.

In order to study the actual energy consumption in the process of clustering and communication, we add energy consumption program in conduct above experiments. The model of energy consumption can be seen in Eq. (2) while other parameters are unchanged. Some additional parameters are shown in the following:

- . Initial Energy is *Eo*=5 in each sensor node;
- $E_{TX} = E_{RX} = 5\times10^{-8}$
- Transmit Amplifier types: $E_{fs} = 10\times10^{-12}$; $E_{mp} = 0.013\times10^{-12}$;

In addition, all experiments are conducted for independent runs for LEACH, LEACH-C and LEACH-DE. Simulation results presented in Table 4 that showed the total remain energy of LEACH, LEACH-C and LEACH-DE after 1000 iterations.

Table 4. Comparison of LEACH, LEACH-C and LEACH-DE in the total remain energy

Protocol	LEACH	LEACH-C	LEACH-DE
Remain energy	36.3	40.67	46.79

The number of CHs in LEACH-DE and LEACH-C are optimal, while that of LEACH is unstable.

From the view of “energy consumption”, it is quite clear that LEACH-DE and LEACH-C are superior to the LEACH. From Table 4, it can be seen that LEACH-DE is about 20% reducing in the energy consumption compared to LEACH. In general, as the convergence value and energy consumption are considered, it is quit obvious that the overall performance of LEACH-DE is better than that of LEACH and LEACH-C.

V. CONCLUSION AND FUTURE WORK

This paper demonstrates LEACH-DE which is the population-based protocol can provide significant improvement in the optimal clustering and network lifetime compared to the traditional routing protocols such as LEACH-C and LEACH. In this work, some preliminary experiments have been performed to verify the performance of LEACH-DE. In addition, we believe that some other excellent swarm intelligence algorithms such as PSO and GA can be used for solving routing problem of WSN. In our future work, the effect will be studied in more detail by varying the position of sensor nodes, creating an efficient ad-hoc net for reducing energy consumption and aggregating data for enhance the performance of WSN.

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