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Energy Efficiency and Maximizing Network Lifetime for WSNs using ACO Algorithm

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Abstract*— Wireless Sensor Networks (WSNs) carry out both monitoring and communication task. WSN's have attractive a great deal of study due to their low cost and wide range applications. A WSN is a distributed system consisting of many small sensor nodes delayed in environments to sense the physical world. WSNs have a large number of applications in real time monitoring, such as battle field surveillance, environment monitor, personal health monitor and so on. The main challenging problem in WSNs is power consumption and maximizing the network lifetime. WSNs is a demanding task, in this paper proposed an ACO based approaches that can be prolonging the network lifetime and minimizing the power consumption. ACO is a well known Meta heuristic inspired by the foraging behavior of real ants. Ants are stochastic constructive procedures that build solutions while walking on a constructive graph. This paper considers the problem of finding the maximum number of connected covers in different WSNs. A number of methods have been proposed for finding one connected cover from a WSN. The connected covers are a more direct way to minimize power consumption and prolong the network lifetime. The proposed approach has been applied to different WSNs. The compared result shows that the performance and efficiency of the approach with LEACH and PARA, ACO is a successful method for maximizing the network lifetime and minimize power consumption.

Index Terms*— Ant colony Optimization (ACO) algorithm, Energy efficiency, LEACH, Network lifetime, PARA, WSNs.

I. INTRODUCTION

WSNs represent one of the most demanding areas in today's electronic industry. These networks are expected to be sovereign, low-power challenging, context aware and flexible [1]. A final application may have more number of sensor nodes spread out in an environment [2], making the distribution and the support of WSNs a complex problem. A WSN is to provide the users with access to the information of interest from the data gathered by spatially distributed sensors. The energy of the sensor nodes is usually supplied by battery with limited energy. The vital to wide applications of WSNs is lower energy consumption and to prolong the network lifetime. A fundamental criterion for evaluating a WSN is the network lifetime [3], which is defined as the period that the network satisfies the application requirements. Since most nodes of WSNs are powered by nonrenewable batteries, studies of prolonging the network lifetime have become one of the most important and challenging issues in WSNs.

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In a WSN where nodes are densely deployed [4], a subset of the nodes can already address the coverage and connectivity issues. The rest of the nodes can be switched to a sleep state for conserving energy, for that reason the lifetime of a WSN can be prolonged by planning the active intervals of nodes, at every point during the network lifetime, the active nodes must form a connected cover to fulfill sensing coverage and network connectivity. The nodes in a WSN carry out both monitoring and communication problems. The monitoring task requires nodes to offer satisfying sensing coverage to the target. The communication task demands nodes to form a connected network for collecting and disseminating information via radio transmissions. The problem of finding the maximum number of connected covers is difficult because each connected cover must fulfill sensing coverage and network connectivity simultaneously. In this paper, a common type of different WSNs is considered and a novel activity planning approach for minimizing power consumption and prolonging the network lifetime is proposed. The approach can be used in both cases of discrete point coverage and area coverage. We focus on the area coverage; the considered WSNs comprise two types of nodes: sensors and sinks. The sensors monitor the target and transmit the monitoring results to the sinks. The sinks relay the monitoring results to the destination. Therefore, a connected covers in the WSNs must satisfy the following three constraints: 1) the sensors form complete coverage to the object. 2) All the monitoring results obtained by the sensors are transmitted to the sinks and 3) the sinks compose a connected wireless network. These three constraints interact with each other as the second constraint involves both sensors and sinks. Finding the maximum number of connected covers is thus more difficult than either the problem of maximizing the number of sensor subsets under the coverage constraint or the problem of maximizing the number of sink subsets under the connectivity constraint. In ACO, ants are stochastic constructive procedures that build solutions while walking on a construction graph. Such useful search behavior makes ACO suitable for solving combinatorial optimization problems. Besides, ACO utilizes search experiences and domain knowledge to accelerate the search process. ACO algorithms have been successful applied to a number of industrial and scientific problems. In this paper proposed an ACO –based routing algorithms used for improving the power efficiency in unicasting [5], transmitting [6, 7] and data gathering [8]. The ACO algorithms that focus on the routing issues in WSNs, for maximizing the lifetime of WSNs by finding the maximum number of connected covers.

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II. RELATED WORK

Wireless Sensor Networks (WSNs) are a novel wireless communication network (WCN), which combine communication technology, embedded computing and sensor technology. It organized by a large number of sensor nodes through wireless medium to connect with each other. Sensor nodes are usually powered by battery, so how efficiently and rationally use energy to extend the network lifetime as much as possible has became one of the core issues of sensor networks [9]. Network routing is the foundation to achieve efficient communication in network, which makes the WSNs routing algorithm has, became a research hotspot in WSNs. LEACH (Low- Energy Adaptive Clustering Hierarchy) [10] is an application specific data dissemination protocol that uses clustering to prolong the network lifetime. However, the algorithm in the process of selecting the cluster head (CH) does not take the residual energy of node into account, which problems that lower energy node may be selected to CH, and all the CHs directly communicate with the base station which will cause the nodes to premature death. In [11], a fully distributed clustering (HEED) has been proposed, the algorithm according to the node's residual energy to select some candidates' CH, and then select the final CH by the level of the cost of the cluster communication. However, this algorithm requires multiple messages with the iteration in cluster radius, and the communication spending is significant. In [12], a distributed routing algorithm based on ANT algorithm for data aggregation has been proposed. The basic idea of the algorithm is that use the artificial agents which known as the "ants" to find the optimal path to reach the target node, and use Positive feedback effect of ANT algorithm to achieve the purpose of data collection. But the algorithm cannot solve the energy load balancing in the network. In [13], the authors proposed ACRA which by modifying the Ant Colony Optimization (ACO). Due to use of the primary path and alternate path, energy consumption and delay had been improvement, but the ants find paths only consider the impact of pheromone, so the ants coverage to the optimal solution that result from congestion and make the energy consumption relatively concentration. In [14], the authors proposed PARA, by taking the energy level and distance of transmission into the pheromone increment formula, so it better used in the WSNs. However, the algorithm does not consider the whole network use the energy stabilize issue. Because the CH nears the base station requires forwarding a lot of data from other CHs which is too heavy to cause the node premature death. Based on the ant colony algorithm (ACA) and clustering routing algorithm in wireless sensor network, we propose a novel uneven clustering routing algorithm for Wireless Sensor Network based on ACO. The algorithm uses uneven clustering algorithm to divide the sensor nodes within the region level to make the clusters closer to sink has smaller scale than those farther away from the sink. After combining the clusters data, the elected CH through the ACO algorithm to find the optimal path. Simulation results show that the routing algorithm can balance the network energy consumption and prolong the network life cycle.

III. ANT COLONY OPTIMIZATION

A combinatorial optimization problem is a problem defined over a set $C = \{C_1, C_2, ... C_n\}$ of basic *components* [15]. A subset **S** represents a *solution* of the problem; $F \leq 2^C$ is the subset of *feasible solutions*, thus a solution **S** is sensible if and only if $S \in F$. A *cost function z* is defined over the solution domain, $Z : 2^C \to R$ the objective being to find a minimum cost feasible solution S*, i.e., to find $S^* : S^* \in F$ and $Z(S^*) \leq Z(S), \forall S \in F$. A set of computational concurrent and asynchronous agents (a colony of ants) moves through states of the problem corresponding to partial solutions of the problem to solve. They move by applying a problematic local decision policy based on two parameters, i.e. *trails* and *attractiveness*. By moving, each ant cumulatively constructs a solution to the problem. When an ant finishes a solution during the development phase, the ant appraises the solution and modifies the trail value on the components used in its solution. This pheromone report will direct the search of the future ants. Furthermore, an ACO algorithm contains two more mechanisms*: trail evaporation* and *daemon actions*. Trail evaporation decreases all trail values over time, in order to avoid unlimited aggregation of trails over some component. Daemon actions can be used to appliance centralized actions which cannot be performed by single ants, such as the command of a local optimization procedure, or the update of global information to be used to decide whether to bias the search process from a non-local perspective [16]. More exactly, an *ant* is a simple computational agent, which iteratively constructs a solution for the occurrence to solve. Partial problem solutions are seen as *states*. At the basis of the ACO algorithm lies a cluster, where at each iteration, each ant *moves* state i to j, corresponding to a more complete partial solution. That is, at each step σ, each ant *k* computes a set $A_k^{\sigma}(t)$ of feasible expansions to its current state, and moves to one of these in probability. The probability distribution is specified as follows. For ant *k*, the probability P_{ij}^k of moving from state i to state j depends on the combination of two values:

- The *attractiveness* η_{ij} of the move, as measured by some heuristic indicating the *a priori* desirability of that move;
- The *trail level* τ_{ij} of the move, indicating how proficient it has been in the past to make that particular move: it represents therefore a *posterior* indication of the desirability of that move.

Trails are *updated* usually when all ants have completed their solution, increasing or decreasing the level of trails corresponding to moves that were part of "good" or "bad" solutions, respectively.

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Ant System

The importance of the original Ant System (AS) [17] resides mainly in being the prototype of a number of ant algorithms which collectively implement the ACO paradigm. The move probability distribution defines probabilities P_{ij}^{k} to be equal to 0 for all moves which are infeasible (i.e., they are in the *tabu* list of ant *k*, that is a list containing all moves which are infeasible for ants *k* starting from state i), otherwise they are computed by means of eq. (1), where α and β are user defined parameters (α ≤ 0, β ≤ 1):

$$P_{ij}^{k} = \begin{cases} \dfrac{\tau_{ij}^{k}.\eta_{ij}^{k}}{\sum\limits_{ij \notin tabu_k} \tau_{ij}^{k}.\eta_{ij}^{k}}, if\ (ij) \notin tabu_k \\ 0, \quad otherwise \end{cases} \tag{1}$$

In formula (1), $tabu_k$ is the *tabu* list of ant *k*, while parameters α and β specify the impact of trail and attractiveness, respectively. After each iteration *t* of the algorithm, i.e., when all ants have completed a solution, trails are updated by means of eq. (2):

$$\tau_{ij}(t) = \rho\tau_{ij}(t-1) + \Delta\tau_{ij} \tag{2}$$

Where $\Delta\tau_{ij}$ represents the sum of the contributions of all ants that used move (ij) to construct their solution, ρ, 0 ≤ ρ ≤ 1, is a user-defined parameter called *evaporation coefficient*, and $\Delta\tau_{ij}$ represents the sum of the contributions of all ants that used move (ij) to construct their solution. The ants' contributions are proportional to the quality of the solutions achieved, i.e., the better solution is the higher will be the trail contributions added to the moves it used. For example, in the case of the TSP, moves correspond to arcs of the graph, thus state i could correspond to a path ending in node *i*, the state j to the same path but with the arc (*ij*) added at the end and the move would be the traversal of arc (*ij*). The quality of the solution of ant *k* would be the length L_k of the tour found by the ant

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \tag{3}$$

Where *m* is the number of ants and $\Delta\tau_{ij}^{k}$ is the amount of trail laid on edge (*ij*) by ant *k*, which can be computed as

$$\Delta\tau_{ij}^{k} = \begin{cases} \dfrac{Q}{L_k}, if\ ant\ k\ uses\ arc(ij)\ in\ its\ tour \\ \qquad 0, otherwise \end{cases} \tag{4}$$

Q is a constant parameter.

$$\Delta\tau_{ij}^{k} = \lambda \times \left(E_i + E_j\right) / d^2(i,j) \tag{5}$$

Where E_i, E_j are the residual energy of the selected node i and j. The ant system simply iterates a main loop where *m* ants construct in parallel their solutions, thereafter updating the trail levels. The performance of the algorithm depends on the correct tuning of several parameters, namely: α, β relative importance of trail and attractiveness, ρ trail persistence, $\tau_{ij}(0)$ initial trail level, *m* number of ants, and Q used for defining to be of high quality solutions with low cost.

Ant Colony System

Ant System was the first algorithm inspired by real ants' behaviour. AS was initially applied to the solution of the travelling salesman problem but was not able to compete against the state-of-the art algorithms in the field. On the other hand he has the merit to introduce ACO algorithms and to show the potentiality of using artificial pheromone and artificial ants to drive the search of always better solutions for complex optimization problems. The next researches were motivated by two goals: the first was to improve the performance of the algorithm and the second was to investigate and better explain its behaviour. Gambardella and Dorigo proposed in 1995 the Ant-Q algorithm, an extension of AS which integrates some ideas from Q-learning, and in 1996 Ant Colony System (ACS) [18, 19] a simplified version of Ant-Q which maintained approximately the same level of performance, measured by algorithm complexity and by computational results. Since ACS is the base of many algorithms defined in the following years we focus the attention on ACS other than Ant-Q. ACS differs from the previous AS because of three main aspects:

Pheromone

In ACS once all ants have computed their tour AS updates the pheromone trail using all the solutions produced by the ant colony. Each edge belonging to one of the computed solutions is modified by an amount of pheromone proportional to its solution value. At the end of this phase the pheromone of the entire system evaporates and the process of construction and update is iterated. On the contrary, in ACS only the best solution computed since the beginning of the computation is used to *globally update* the pheromone. As was the case in AS, global updating is intended to increase the attractiveness of promising route but ACS mechanism is more effective since it avoids long convergence time by directly concentrate the search in a neighbourhood of the best tour found up to the current iteration of the algorithm. In ACS, the final evaporation phase is substituted by a *local updating* of the pheromone applied during the construction phase. Each time an ant moves from the current city to the next the pheromone associated to the edge is modified in the following way: $\tau_{ij}(t) = \rho.\tau_{ij}(t-1) + (1-\rho).\tau_0$ where 0 ≤ρ≤ 1 is a parameter (usually set at 0.9) and τ_0 is the initial pheromone value. τ_0 is defined as $\tau_0 = (n \cdot L_{nn})^{-1}$, where L_{nn} is the tour length produced by the execution of one ACS iteration without the pheromone component (this is equivalent to a probabilistic nearest neighbour heuristic). The effect of local-updating is to make the desirability of edges change dynamically: every time an ant uses an edge this becomes slightly less desirable and only for the edges which never belonged to a global best tour the pheromone remains τ_0. An interesting property of these local and global updating mechanisms is that the pheromone $\tau_{ij}(t)$ of each edge is inferior limited by τ_0. A similar approach was proposed with the Max-Min-AS (MMAS) [20] that explicitly introduces lower and upper bounds to the value of the pheromone trials.

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State Transition Rule

During the construction of a new solution the state transition rule is the phase where each ant decides which is the next state to move to. In ACS a new state transition rule called *pseudo-random-proportional* is introduced. The *pseudo-random proportional* rule is a compromise between the *pseudo-random* state choice rule typically used in Q-learning and the *random-proportional* action choice rule typically used in Ant System. With the pseudo-random rule the chosen state is the best with probability q0 (exploitation) while a random state is chosen with probability *1-q0 (exploration).* Using the AS random-proportional rule the next state is chosen randomly with a probability distribution depending on η_{ij} *and* τ_{ij}. The ACS *pseudo-random-proportional* state transition rule provides a direct way to balance between exploration of new states and exploitation of a priori and accumulated knowledge. The best state is chosen with probability *q0 (that is a parameter $0 \leq q_0 \leq 1$ usually fixed to 0.9)* and with probability *(1-q0)* the next state is chosen randomly with a probability distribution based on η_{ij} and τ_{ij} weighted by α (usually equal to 1) and β (usually equal to 2) .

$$S = \begin{cases} \arg\max\limits_{(ij)\notin tabu_k} (\tau_{ij}^{\alpha} . \eta_{ij}^{\beta}), if\ q \prec q_0 & (\exp loitation) \\ AS\ rule\ 1, \quad otherwise & (\exp loration) \end{cases} \tag{6}$$

Hybridization and performance improvement

ACS was applied to the solution of big symmetric and asymmetric travelling salesman problems (TSP/ATSP). For these purpose ACS incorporates an advanced data structure known as *candidate list*. A candidate list is a static data structure of length *cl* which contains, for a given city *i*, the *cl* preferred cities to be visited. An ant in ACS first uses candidate list with the state transition rules to choose the city to move to. If none of the cities in the candidate list can be visited the ant chooses the nearest available city only using the heuristic value η_{ij}. ACS for TSP/ATSP has been improved by incorporating local optimization heuristic (*hybridization*): the idea is that each time a solution is generated by the ant it is taken to its local minimum by the application of a local optimization heuristic based on an edge exchange strategy, like 2-opt, 3-opt or Lin-Kernighan [21]. The new optimized solutions are considered as the final solutions produced in the current iteration by ants and are used to globally update the pheromone trails. This ACS implementation combining a new pheromone management policy, a new state transition strategy and local search procedures was finally competitive with state-of-the-art algorithm for the solution of TSP/ATSP problems.

Clustering

The main function of cluster route stage is to transmit data. In order to achieve multi-hop communication between the clusters, and reduce the energy consumption of the CH which away from the base station, using the ant colony optimization algorithm to find the optimal path between the CH. CH through the optimal path to transmit data to reduce the energy consumption, and extend the network life cycle.

Election of Cluster head

In the CH election process, the sensor node firstly generates a random number between 0 and 1, and if less than the threshold T (n), then this node becomes the candidate CH. In each round of the loop, if the node is elected as the CH, put T (n) set to 0, so that the node will not be re-elected as CH. We modify the equation of T (n) as follows:

$$T(n) = \begin{cases} \dfrac{P}{1 - P * \left(r \bmod (1/p)\right)} \times \dfrac{E_{residual}}{E_0}, & n \in G \\ 0 \qquad , & otherwise \end{cases} \tag{7}$$

The Formation of Cluster

Once the node through the above calculation to become the CH, according to the distance *d* which is calculated in the cluster formation stage to calculate the size of the cluster radius *c R* . The equation of *c R* is given by

$$R_c = \left(1 - c\frac{d_{\max} - d(s_i, DS)}{d_{\max} - d_{\min}}\right) R_0 \tag{8}$$

Where: *c* is to control the range of parameters, the range between 0 and 1; $d_{\max}$ and $d_{\min}$ are the network nodes to the base station's maximum and minimum distance; $d(s_i, DS)$ is the distance between node s_i to the base station; R_0 is the maximum range of the cluster. According to eq. (8), the closer to base station, R_c is smaller. Once R_c is chosen, each candidate CH broadcasts competitive news to nodes within its clusters, if there is no other candidate CH, the node announces as the CH, and broadcast competitive success message. If there is other candidate CH within its clusters, then compare the residual energy with other nodes, the nodes that has the largest residual energy becomes the final CH and broadcast success news. After the CH is identified, other nodes according to the received signal strength to determine subordinate cluster, and inform the appropriate CH. When the CH receives the news, it uses the TDMA method to assign time slot for the nodes to send data, and then the cluster is completed.

Algorithm Design

- State initialization: placing K ants to each CH, initialize the number of hops *JNum* =1, the number of iteration $R_{\max}$ =*C* (constant), set and initialize three matrices *Tabu R_best* and *A_city* , *Tabu* is used to store and record the generated path, *R _ best* is used to store the best path for CH, *A_ city* is used to store the visited node, the pheromone matrix *Tabu* is initialized to matix (*n*,*n*) .
- Insert the visited nodes into *A_city*, each ant searches the next hop by the probability calculation, and updates *A_city* and*Tabu* .
- Updating the pheromone values on the path by ant move from node i to node j.
- Determine each ant whether to meet the iteration termination condition. If the ant does not meet the conditions, then return to step 2 to continue the search algorithm, such as to meet the conditions, then save the current optimal solution.

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IV. SIMULATION RESULTS

A. Energy Model and Parameters

In this paper, we use the same energy model and wireless transmitter module can control the size of the transmit power, according to the distance between the nodes. We constructed an event driven simulator by using MATLAB. The specific simulation environment: In the network, 200 sensor nodes are randomly distributed on a M×M region with M=200m. the coordinate of the base station is (100,350), *PacketLength* =4000, *ctrPacketLength* =100, R_s =20 m, E_{DA}=0.5nJ/bit, E_{elec}=50nJ/bit, ε_{fs} =10 pJ/(bit$\cdot m^2$), ε_{mp} =0.0013 pJ/(bit$\cdot m^4$), d_0 =75m, c =0.5, E_0 =0.5J, R_0 =30m, α=2, β =2, λ_1 =2, λ_2 =1, λ_3 =1, ρ =0.2

B. Analysis of Simulation

Figure 1 presented the comparison of the simulation for the average energy consumption of the node with the rounds between LEACH, PAPA and our algorithm. The total energy of 200 nodes are 100J, the nodes are all killed at 1150 rounds in LEACH, which consumes energy is 100J, PARA consume energy is 80J, our algorithm is 55J, which reduce 45J, so that performance of the network has been greatly improved, and the energy consumption is more evenly distributed to all nodes.

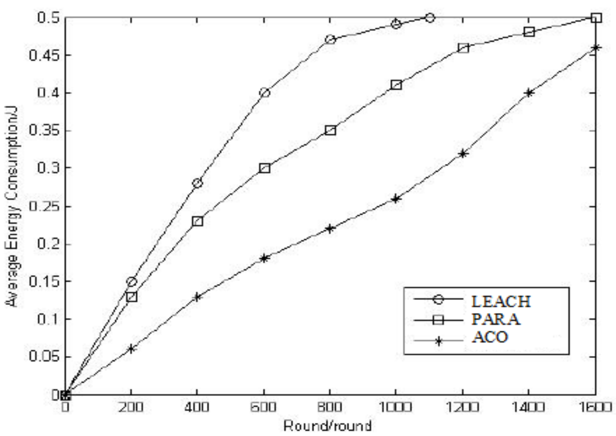

Figure 1. Average Energy Consumption

Figure2 presented the results of the simulation for the survival rate of the nodes with the rounds. The survival rate of PARA significantly improved compared to LEACH, while showing a lower survival rate of the nodes relatively compared with our algorithm. The reason why this happens is that LEACH does not consider the residual energy of the nodes when selecting the CH and CH directly communicate with base station, and then excessively consume the energy of the CH. Although PARA used the ant colony optimization algorithm to transmit data in multi-hop, it does not consider the balanced energy consumption of the whole network. So that the CH near the base station will transmit large amount of data, and will be premature death.

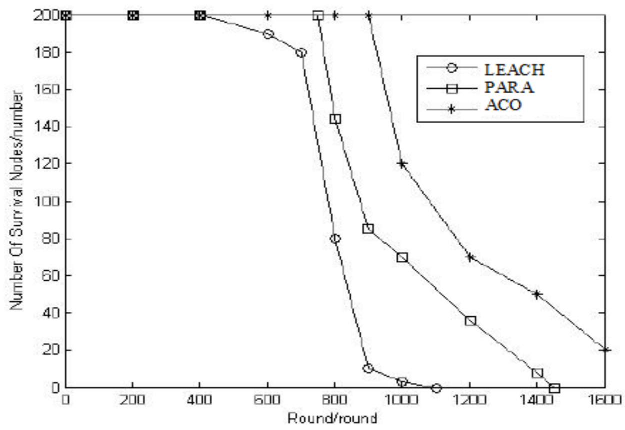

Figure 2. The Survival Rate of Node

V. CONCLUSION

In this paper we have illustrated a homogeneous clustering based ACO algorithm for wireless sensor network that saves energy and maximize network lifetime. The lifetime of the network is increased by ensuring a homogeneous distribution of nodes in the clusters. A new cluster head is selected on the basis of the residual energy of existing cluster heads, holdback value, and nearest hop distance of the node. The homogeneous algorithm makes sure that every node is either a cluster head or a member of one of the clusters in the wireless sensor network. In the proposed clustering ACO algorithm the cluster members are uniformly distributed, and thus, the life of the network is more extended. Further, in the proposed protocol, only cluster heads broadcast cluster formation message and not the every node. Hence, it maximize the lifetime of the sensor networks. Battery power being scarce resources of sensors, energy efficiency is one of the main challenges in the design of protocols for WSNs. The ultimate objective behind the protocol design is to keep the sensors operating for as long as possible, thus extending the network lifetime. The factors affecting cluster formation and CH communication are open issues for future research. This investigation will be highly useful for energy efficient wireless sensor network. Ant colony optimization algorithm is used to optimize the path on that the CH to transmit the data. The simulation results show that compared with LEACH and PARA, our algorithm has significantly improved in average energy consumption and survival rate, and extended the network lift cycle.

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