Maximum Lifetime Routing Based on Fuzzy Set Theory in Wireless Sensor Networks

Jianhui Li, Guiping Liao*, Fang Wang, Jinwei Li
Institute of Agricultural Information, Hunan Agricultural University, Changsha, China
Email: jamesmark.li@gmail.com, lgpxf@yahoo.com.cn, topwang619@163.com, wucao9371@163.com

***Abstract*—To solve the problem of energy saving in the design of wireless sensor networks, a new maximum lifetime routing algorithm was proposed based on uneven cluster, linear programing and fuzzy set theory (UCLF) in wireless sensor networks, which formulated the system maximum lifetime problem as a linear programming problem and selected cluster head based on fuzzy set theory, where the objectives is to output optimal clusters which closer to the sink node have fewer nodes than those farther away from the sink node and seek a balance point between energy consumption and routing efficiency to maximize the network lifetime. Compared with the classical energy efficient algorithm, such as CMAX, simulation results show that UCLF can effectively extend the network lifetime.**

***Index Terms*—Wireless Sensor Networks; Uneven Clustering; Linear Programming; Fuzzy Set Theory**

I. INTRODUCTION

Comparing with frequently moving of nodes in the traditional wireless ad hoc networks, wireless sensor networks (WSN) are usually consisted of a large number of static sensor nodes with limited energy. Many small sensor nodes powered by limited batteries are randomly distributed which work together as a sensor network and transfer information generated by source nodes to base station over several hops. As wireless sensor networks are deployed in the complex environment, in general, the batteries are difficult to replace or recharge. Hence, efficient use of energy resources and prolonged lifetime of a network are very important issues in wireless sensor networks. Energy consumption in the wireless sensor networks can be closely related with three modules, sensor module, data processing module and wireless transceiver module. Among these three, most energy was consumed on wireless transceiver module.

Several related works on energy conservation routing technology in wireless sensor networks have deal with the problem of reducing the amount of data traffic, and resulting in higher energy saving[1]-[6]. These protocols include flat and hierarchical routing protocols. The authors presented a flat routing protocol named SPIN which reduces the spread of information via negotiations between the nodes [1, 2]. Heinzelman et al. proposed LEACH protocol for the first time, which is the data aggregation-based hierarchical routing protocol [16]. In LEACH, each node generates a random number $p \in [0,1]$, if p is less than a certain threshold $T(n)$, the node becomes a cluster head in this election competition. Sensor nodes transmit their collect data to designated cluster heads. These cluster heads send their gathered datum to base station by one hop too. Manjeshwar et al. developed TEEN [7] protocol based on the typical clustering-based routing protocol LEACH.TEEN reduces the amount of sensor nodes state traffic that is propagated regularly. From what has been discussed above [3]-[6], clustering-based multi-hop routing protocols are considered as the best energy conservation routing technology in WSN. However, this way brings a new problem of imbalance energy consumption of node battery power while cluster heads closer to the base station tend to die earlier because more data packets are needed to transmit [8]. So the researchers present some methods based on energy-efficient uneven clustering algorithm, such as EEUC, CEBUC etc. [9, 10], which can generate network topology of optimum number of clusters. The closer to base station a cluster is, the smaller size it will be. Thus, those cluster heads can preserve some energy for the inter-cluster data forwarding. The uneven clustering algorithm is a useful complementary to our work.

The problem of the network lifetime is also defined the time of the first node death, while it exists successful routing from source node to destination node, i.e., the maximum lifetime routing problem equals to calculate optimum routing cost between energy consumption and shortest routing path. Most of previous researches are based on either finding maximum path energy or minimum route hops. A. Misra et al. proposed the MRPC and CMRPC algorithm which attempt to select on a maximum energy path as system maximum lifetime [11]. In MRPC, the path that has the largest packet capacity is selected. The capacity is defined $C_{i,j}$ equaling to $B_i / E_{i,j}$, where B_i is the residual battery capacity of node i, $E_{i,j}$ is the transmission energy required by node i to transmit a packet over *link* (i, j) to node j. C. Toh et al. have presented the MMBCR and CMMBCR which select a routing path for which the minimum of the residual energy of the sensors on path as maximum [12]. Kar K et al. proposed the CMAX algorithm [13], which the routing objective is to maximize the total number of messages

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that can be successfully sent over the network without knowing any information regarding future message arrivals or message generation rates. Note the worst-case performance of CMAX algorithm is within a factor of $O(\log\ (network\ size))$ of the best achievable solution, if admission control of messages is permitted.

Based on the previous works, we try to focus on optimal balance point between energy consumption and routing efficiency to maximize the network lifetime. It is important to avoid the nodes with small residual energy on the routing path. Therefore, the maximum lifetime of network is to find the sum of routing path that all message generated by source nodes can reach the corresponding destination. The UCLF presented in this paper has some advantages as follows. For one thing, a novel uneven clustering algorithm for Wireless Sensor Networks can effectively alleviate the "hot spot" issues, in which cluster head is selected by using fuzzy set theory, which takes the residual energy nodes intensity and distance from sink node as the important index. For another, the system maximum lifetime is transformed to a sequential linear programming based on fuzzy set theory. Finally, a hierarchical routing tree with base station as the root is established according to the hop and energy-level of cluster heads. The above are innovations.

This paper is organized as follows. The section 2 introduces the mathematic model and terminology of algorithm. In section 3, a new maximum lifetime routing algorithm based on uneven cluster, linear programming and fuzzy set theory (UCLF) was proposed. The process about setting up cluster and selecting routing path are introduced in detail. In section 4, we evaluate UCLF using simulations on NS2 platform. In this section [15], the performance of UCLF is compared with CMAX. The experiment results show our UCLF is superior to CMAX. In section 5, some conclusions are concluded.

II. Model and Terminology

In this section, for convenience, thereinafter, we make following assumptions:

A. Reference Radio Model

First, we adopt the first order radio model for energy consumption computation1. Figure1 gives the model.

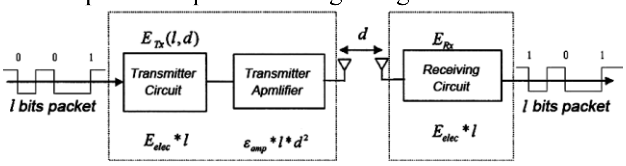

Figure 1. First order radio model

In this model, E_{RX} is the energy consumption during l bits packet message reception. Then,

$$E_{RX} = E_{elec} * l \quad (1)$$

$E_{TX}(l,d)$ denotes the energy require to do l bits packet message transmission, i.e.,

$$E_{RX} = E_{elec} * l \quad (2)$$

E_{elec} is the energy consumption during 1bit packet message reception or transmission in circuit, and E_{amp} is the energy consumption in transmitter amplifier circuit. In Figure 1, d denotes distance between source nodes and destination nodes, r is a non-negative integer coefficients, $r \in [2,4]$. For now, according to the above formula (1) and (2), the total energy consumption $E_{i,j}(l,d_{i,j})$ can be calculated by formula (3) during the period of transmission l bits packet message from node i to node j (distance between them is d)

$$E_{i,j}(l,d_{i,j}) = E_{RX} + E_{TX}(l,d_{i,j}) = l(2E_{elec} + E_{amp} * d^{\gamma}_{i,j}) \quad (3)$$

In order to focus our attention on the main problems, we assume no energy consumption during message reception. Thus, the total energy consumption $E_{i,j}(l,d_{i,j})$ can be calculated by formula (4), i.e.

$$E_{i,j}(l,d_{i,j}) = E_{TX}(l,d_{i,j}) = l(E_{elec} + E_{amp} * d^{\gamma}_{i,j}) \quad (4)$$

B. The topology of the WSN

Next, the sensor nodes in the WSN are fixed and the topology of the WSN is static, and the sink node is on the extender side of specified regions with unlimited power supply. Signal of sink node can cover everywhere in WSN. We make the assumption that the radio channel is symmetric such that the energy required to transmit a message from node A to node B is the same as the energy required to transmit a message from node B to node A. Each node can compute the distance from sink nodes judging by the signal intensity obtained. Clustering sensors into groups, so that sensors communicate information only to cluster heads and then the cluster heads communicate the aggregated information to the sink node. Figure 2 shows how inner-cluster and inter-cluster communication process. We assume the inner-cluster communication is single-hop and inter-cluster communication is multiple-hop. Our following discussion is mainly about inter-cluster communication.

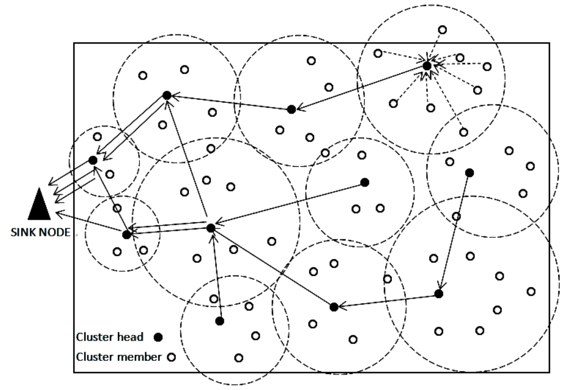

Figure 2. Inner-cluster and inter-cluster communication

C. Logical Model

Finally, the amount of information messages of each transmission is a constant equaling l. Previous discussion shows that the maximum lifetime of the network is related to select maximum lifetime routing path. Hence, WSN can be modeled as a directed graph $G(v,e)$, where v is the set of all cluster heads and e is the set of all directed edges $(i,j)\in E$ if and only if the information message generated from node i can reach node j with a certain energy consumption $E_{TX}(l,d_{i,j})$. Each node $i(i\in v)$ is given the initial energy $E_i>0$. After transmission l bits message from node i to j, the residual energy in node i becomes $E_{cu}=E_i-E_{TX}(l,d_{i,j})$. Note only when $E_{cu}>E_{TX}(l,d_{i,j})$, the transmission from node i to j is possible. In the following paragraph, we will describe a maximum lifetime routing problems in WSN as the sum of all successful and maximum lifetime routing sequence.

III. MAXIMUM LIFETIME ROUTING ALGORITHM BASED ON UNEVEN CLUSTER, LINEAR PROGRAMMING AND FUZZY SET THORY (UCLF)

Our objective is to find a path for each routing pair with the best energy consumption cost to the maximization of the system lifetime. Accordingly, we develop a novel maximum lifetime routing algorithm based on uneven cluster, linear programming and fuzzy set theory (UCLF).For ease of presentation, and the algorithm is divided into 3 stages.

A. Stage 1: uneven clustering

Stage 1 –In the first stage, we attempt to accomplish the objective of clustering sensor nodes into uneven clusters in WSN. The process is distributed into rounds, where each round begins with a set-up phase t_{head} when the clusters are organized, followed by a steady-state phase t_{data}, when data transfers to the sink node occur, and assure $t_{data}\geq t_{head}$ to minimize overhead.

Initially, sink nodes broadcast a sequence of message packets to all nodes with different power in WSN. Then the distances $\mu_i(i\in N)$ between sensor nodes and sink nodes are obtained based on the propagation loss model and received signal strength indicator (RSSI). The WSN were divided into several control zones $\alpha_i(i\in N)$ according to those distances, where reduce the energy consumption among nodes by using different transmission power. The process can be illustrated as shown in Figure 3.

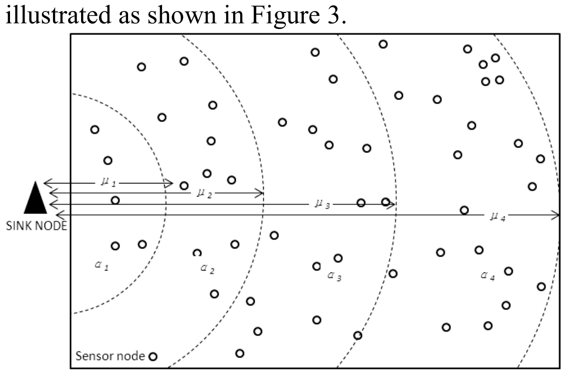

Figure3. Dividing WSN into several control zones

In each control zones, each node decides whether or not to become a cluster-head for the current round. This decision is based on the number of the active neighboring nodes, the performance of residual energy and the distance from sink node. Those nodes which have the less neighborhood nodes and high residual energy and farer distance will have more chances to be the cluster heads. In the proposed algorithm, the sensor nodes elect themselves as control zones α_i cluster heads with probabilities $N.p$. Probability of selection cluster head is obtained from fuzzy inference method given by function *infer*( ). Then, each node will broadcast an advisement packet to their neighbor nodes. The advisement packet has a structure with node identify flag and the probability value. Any sensor node that receives such advertisements will analysis the packet and compares the probability with itself. The sensor node with higher probability becomes a cluster head and advertises itself as a cluster head to the sensor nodes within its radio range R_C given by , where any sensor node except cluster head joins the cluster of the closet cluster head. The pseudo code for clustering algorithm is given, as figure 4 shows.

```
initial
α_i ← div(μ_i)  (i ∈ N)
r ← Random(0,1)
if r < threshold(T) then
N.p = infer(energy, number, distance);
multicast_pkt (ID, N.p, Rc);
end if
while Received multicast_pkt from neighbor node i
if N.p < Ni.p
N.p = null;
end if
end while
if N.p != null
multicast_headinfo(ID, Head);
else
receive multicast_headinfo(ID, Head);
send(ID, Join_Msg) to ClosetHead
end if
```

Figure4. Pseudo code of uneven clustering processing

The principle of fuzzy logic approach to cluster head selection algorithm is described as follows: three main factors of cluster selection are the node's residual energy and the number of neighbor nodes and the distance from sink node, each factor is divided into 3 levels. Considering the expert experience and the three factors mentioned above, 27 fuzzy logic rules are defined. These rules are used to gain the probability of each node, of which these nodes with the maximal probability will be selected as clusters. The fuzzy linguistic variable is summarized in Table Ⅰ for reference.

TABLE I. THE FUZZY LINGUISTIC VARIABLES AND VALUE RANGE

Linguistic variable: residual energy, ω		
Linguistic value	symbol	Range of value
low	L	[0, 0.2]
Medium	M	[0.1, 0.5]
High	H	[0.4, 0.8]
Number of neighbor nodes, s		
Linguistic value	symbol	Range of value
Small	S	[0, 0.40]
Medium	M	[0.30, 0.65]
Large	L	[0.60, 1]
Distance from the sink node, ρ		
Linguistic value	symbol	Range of value
Near	N	[0, 0.40]
Medium	M	[0.35, 0.70]
Far	F	[0.60, 1]
Probability of selection cluster head, p		
Linguistic value	symbol	Range of value
Very Low	VL	[0, 0.25]
Low	L	[0, 0.40]
Rather Low	RL	[0.25, 0.45]
Medium	M	[0.30, 0.70]
Rather High	RH	[0.50, 0.75]
High	H	[0.65, 1]
Very High	VH	[0.75, 1]

In this case, since the model have three input variables and one output variable, the fuzzy rules is conveniently expressed in the fuzzy associative memory (FAM) matrix form, as the figure 5 show.

s \ ω	L	M	H
L	M	L	VL
M	RH	RL	L
S	VH	H	M

Figure 5. Fuzzy rules set was expressed in FAM matrix

By using Mamdani algorithm of fuzzy reasoning [14], 27 items of fuzzy inference rules are generated in the fuzzy system, as the following Table Ⅱ below.

TABLE II. FUZZY RULES SET

No.	ω	s	ρ	n	No.	ω	s	ρ	n
	if			then		if			Then
1	L	S	N	VL	15	H	M	M	RH
2	M	S	N	L	16	L	L	M	RH
3	H	S	N	RL	17	M	L	M	H
4	L	M	N	RL	18	H	L	M	VH
5	M	M	N	M	19	L	S	F	VL
6	H	M	N	RH	20	M	S	F	L
7	L	L	N	RH	21	H	S	F	RL
8	M	L	N	H	22	L	M	F	RL
9	H	L	N	VH	23	M	M	F	M
10	L	S	M	VL	24	H	M	F	RH
11	M	S	M	L	25	L	L	F	RH
12	H	S	M	RL	26	M	L	F	H
13	L	M	M	RL	27	H	L	F	VH
14	M	M	M	M					

By using Min-max T norms to combination the fuzzy rules and geometric center recognition (COG) defuzzification mechanism, we can obtain the accurate probabilities of selection cluster head. The mathematical expression of COG is given as the following.

$$COG = \frac{\int_a^b u_A(x)xdx}{\int_a^b u_A(x)dx} \tag{5}$$

The formula (5) indicates an output of membership function u(x) on the accuracy of interval estimation [a, b] in fuzzy rules set A.

After clusters are organized, time division multiple access (TDMA) is executed by both cluster-head and member node to perform transmission, which is the same as LEACH [4], the repetitious details need not be given here.

B. Stage2: minimum edge number of directed graph

Stage2 –at the beginning of the second stage, the network that consists of all cluster heads is modeled as a directed graph $G(v, e)$. The overall objective in this stage is to get optimized directed graph through pruning graph G with loop.

Deleting all $edge(i, j)$ from G when the single-hop transmission can't not complete, i.e. $E_{Cu} \le E_{Tx}\left(l, d_{i,j}\right)$. Accordingly, the new directed graph $G' = (v, e')$ can be constructed in which we can use Dijkstra's algorithm to compute the minimum energy route path β if β exists [17]. Then, G' is continued to be pruned. Let $E_{\min}$ is the minimum E_{cu} for each node in G' . $G'' = (v, e'')$ is obtained from G' by deleting all $edge(i, j)$ whose $E_{Cu} - E_{Tx}\left(l, d_{i,j}\right) < E_{\min}$. The residual energy of edges pruned from G' may be enough, but it'll be benefit that all nodes can have uniform power consumption in the long run.

C. Stage3: find maximum lifetime routing path

Stage 3 –In the last stage, we design the optimized weights function to compute routing path. It's more important to avoid consumption energy from sensor nodes with small residual energy. Once a node exhausts its energy will affect the performance of the whole network. Therefore, When the residual energy of node i becomes smaller, the $edge(i, j)$ should be given more weight. The weight $COST_{ij}$ assigned to $edge(i, j) \in e''$ is shown in (6).

$$COST_{ij} = E_{Tx}\left(l, d_{i,j}\right) * \lambda \ln(\sigma(i)+1) \quad (6)$$

Among formula (6), the term *λ* is a nonnegative constant and algorithm parameter. By means of adjusting the value of *λ*, the applicability of algorithm to different network environment is improved. For each node, the term $\sigma(i)$ is defined as formula (7). By using $\sigma(i)$, the path rejects the nodes whose residual energy is much less than $E_{\min}$ as relay nodes.

$$\sigma(i) = \frac{E_{\min}}{E_{cu}} \quad (7)$$

It's very obvious that the problem is a linear programming problem [18]. The problem of maximum lifetime routing is equivalent to the following linear programming problem:

$$\begin{aligned} & Maximize\, T \quad (8) \\ & s.t.\, E_i > 0,\ E_{Tx}\left(l, d_{i,j}\right) > 0, \forall i \in v, \forall j \in v \\ & \sum E_{Tx}\left(l, d_{i,j}\right) \le E_i,\ E_{cu} > 0, E_{Cu} \ge E_{Tx}\left(l, d_{i,j}\right), \\ & \forall i \in N, \forall j \in N \\ & \sum E_{min} \le E_i,\ E_{min} \ge 0. \end{aligned}$$

The lifetime of a network for request sequence is equivalent to find all successful routing paths. Hence, the problem can be expressed as the model of the multiple objective programming based on fuzzy set theory.

$$\begin{aligned} & Min\, z = y \quad (9) \\ & s.t. -c_j x - e_j y \le -g_j, \forall j \in N \\ & A_i X - d_i y \le b_i, \forall i \in N, \\ & y \le 1,\ x \ge 0,\ y \ge 0 \end{aligned}$$

Among (9), y= $\sum_i^j COST_{ij}$ .The following steps, we give a dual Simplex method for solution of formula (9).

Let ROW be the rows of the *A-Matrix*, and let COL be the columns of the $A-Matrix$. The $TARG$ is the number of targets. e_j is the range of acceptable bias of target $j, j \in \{1,2,\ldots,TRAG\}$ .Let $A-Matrix$ d_i be the range of acceptable bias of target $i,\ i \in \{1,2,\ldots,ROW\}$ *and* C_{ji} be the weight coefficient through l variables by target $j, j \in \{1,2,\ldots,TRAG\},\ l \in \{1,2,\ldots,ROW\}$. g_j is the expected value of target $j, j \in \{1,2,\ldots,TRAG\}$ *, and* a_{ij} is the elements of the $A-Matrix$, $i \in \{1,2,\ldots,ROW\}, j \in \{1,2,\ldots,TRAG\}$. b_i is the *ith* boundary constraints, $i \in \{1,2,\ldots,ROW\}$ .Then, the definition $A-Matrix$ is given as following,

$$A[0..M, 0..N] = \left|\begin{array}{c|ccc|ccc} a_{00} & a_{01} & \cdots & a_{0.N-M} & a_{0.N-M+1} & \cdots & a_{0N} \\ \hline a_{10} & a_{11} & \cdots & a_{1.N-M} & & & \\ \vdots & \vdots & & \vdots & & & \\ a_{10} & a_{M1} & \cdots & a_{M.N-M} & & & \end{array}\right. \quad (10)$$

Note that $M = ROW + TRAG$ and $N = COL + 1 + M$ is given in *formula (10)*. $C = \left(a_{01,} \ldots, a0.N_{-M}\right)$ is weight vector of target function in formula (9). And $B^T = \left(a_{10}, \ldots, a_{M0}\right)$ is the vectors with constrains of formula (9). Now, the work is finished.

Finally, we summary the running processes of UCLF algorithm mentioned above, as the Figure 6 shows.

*Step*1: [*uneven clustering*]

Divided WSN into several uneven control zones $\alpha_i\left(i \in N\right)$ according to the distances μ_i .

Selected cluster heads in their respective control zones by using fuzzy set theory.

*Step*2: [min*imum edge number of directed graph*]

Deleting all *edges* (i, j) from G , when $ECu \le ETx\left(l, d_{i,j}\right)$. G' is obtained.

Compute the minimum energy route path β if β exists.

Deleting all *edges* (i, j) from G' , when $E_{Cu} - E_{Tx}\left(l, d_{i,j}\right) < E_{\min}$. G'' is obtained.

*Step*3: [*find* max *imum lifetime routing path*]

The weight $COST_{ij}$ assigned to edge (i, j) in G'' .

Compute the shortest route path β if β' exists in G'' .

Use β' for the route.

Figure 6. 3 stags of UCLF algorithm

Note that in practice, because of limited energy, it's hard for each node to recognize complete information including current energy levels of all sensors and the topology of the WSN. Aslam et al. proposed a hierarchical zone-based strategy that is worth to use for reference [16]. Zone-based routing is a hierarchical approach in which the area covered by the (sensor) network is divided into a small number of zones. There is a high level residual energy sensor named host node (the host node will be on duty by turns) responsible for global routing in each zones by using limited flooding approach. These host nodes were modeled as new directed graph. Each node itself isn't host node can report or obtain global information from host node. The distributed algorithm may apply to our UCLF as well.

IV. PERFORMANCE EVALUATION

In this section, we evaluate the performance of UCLF algorithm through simulations on NS2 platform.

Comparison is made with CMAX algorithm as well, since CMAX algorithm has a better performance than other algorithms such as MPRC and max-min zP_{min}, etc [16]. We consider a network of 20~100 nodes located randomly in a100×100 grid regions, as shown in Figure 7.

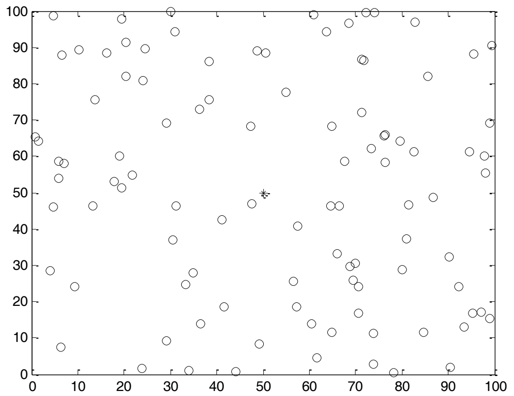

Figure 7. Map of 100 distributed nodes

The initial energy of each node is 30 units. We assume that all messages are of unit length, and are generated randomly between all source-destination pairs. The energy required for transmitting a message along an $edge(i, j)$ is $max\left(0.001, 0.001 * d_{i,j}^{\ 3}\right)$, where $d_{i,j}$ is the distance between nodes i and j. This is similar to the kind of networks studied in reference [13]. The first order radio model is our reference model. In this model, energy $(E_{elec} = 50nj / bit)$ is consumed by transmitter and receiver circuits, amplification index of channel model based on free space loss is $10nJ / bit / m^2$ denoted by ξ_{fs}, amplification index of channel model based on Multipath Fading is $0.0013pJ / bit / m^4$ *denoted by* E_{amp}, energy $\left(E_{da} = 5n\ J / bit / signal\right)$ is consumed by data aggravation. The detail characterization of network simulation is described in Table III.

TABLE III. THE CHARACTERIZATION OF NETWORK SIMULATION

Network model		Radio model	
Parameter	Value	Parameter	Value
$Region$	100×100	E_{elec}	$50nj / bit$
$Number\ of\ nodes$	$20 \sim 100$	E_{amp}	$0.0013\ pJ / bit / m^4$
$Location\ of\ Sink\ node$	$(75, 200)$	E_{da}	$5n\ J / bit / signal$
$Initial\ energy$	30	ξ_{fs}	$10\ nJ / bit / m^2$
$Unit\ Length$	$2000bits$	$d_0 =$	$90m$
$Degree\ of\ Data\ fusion$	0.5	P: *probability of clustering*	5%

In our experimental, we select the algorithm parameter $\lambda = 10^{10}$ for both UCLF and CMAX, which is similar to that employed by Kar et al [13].

First of all, we study the effect of sensor density on performance. Let the transmission radius of sink node (in UCLF) or sensor node (in CMAX) vary from 30 to 100, other parameters as table 3 show. In this study, we prepared 500 test cases and 200 random request sequences in 25 random placements. Figure 8-10 showed average lifetime between UCLF and CMAX. From this experiment, we could observe that in all cases, UCLF was the better under both density conditions. For example, when n=30 and transmission radius is 90, the average lifetime using UCLF is 23.7% larger than that using CMAX. The percentage becomes 33.4% at n=100 and at the same radius, etc.

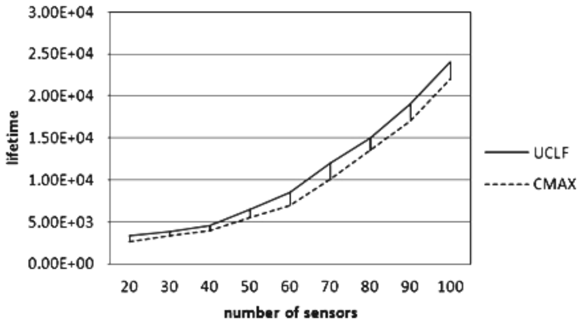

Figure 8. Average lifetime when transmission radius is 30

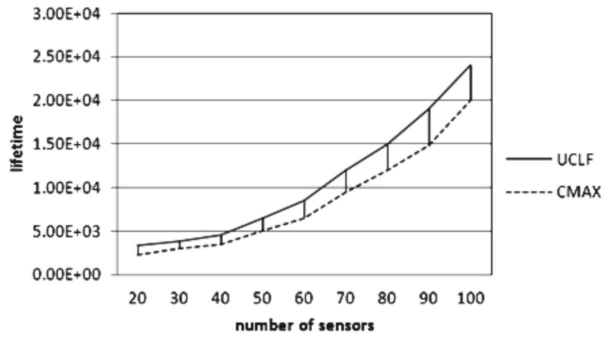

Figure 9. Average lifetime when transmission radius is 60

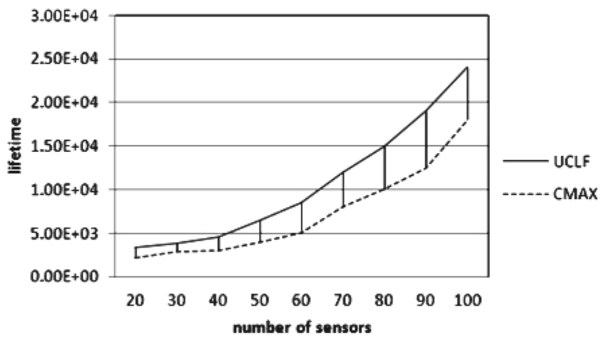

Figure 10. Average lifetime when transmission radius is 90

Next, we compare the number of nodes alive between UCLF and CMAX after running a period of time. In this scenario, we generated 10 networks by randomly placing 100 sensor nodes in a 100×100 grid, each node started with 10 units of energy and node's transmission radius was ∞. For each of 10 networks, 20 request sequences of size 10,000 each were tried. The remaining parameters were as used in our previous experiments.

A few of sensor nodes exhausted its energy and became dead nodes after a period of network operation. In the following illustrations, such as Figure 11-12, it's obvious that amount of dead nodes has gone up considerably in the running stag both in UCLF and CMAX. The Figure 11-12 indicated the node-state at the point of 60% of the whole experimental running.

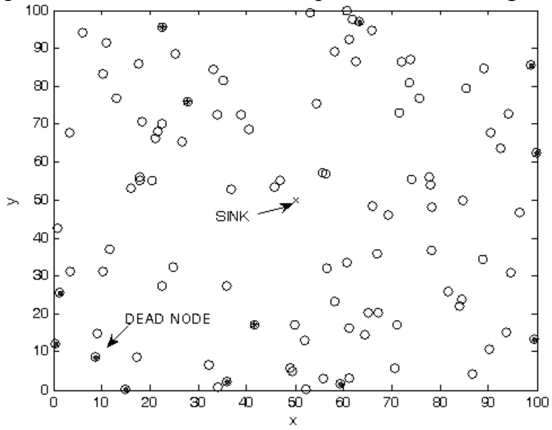

Figure 11. Node-state in UCLF after 60% of running

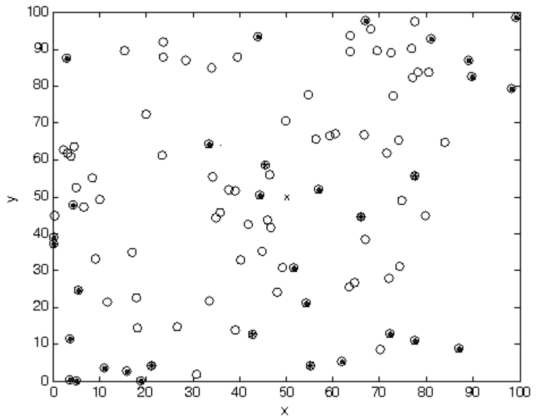

Figure 12. Node-state in CMAX after 60% of running

The end results of this experiment comparing between UCLF and CMAX are depicted in Figure 13.

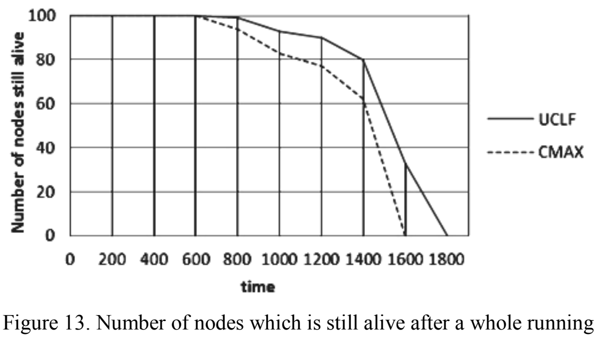

Figure 13. Number of nodes which is still alive after a whole running

AS shown in Figure13, the average time of first node death using UCLF is 25% larger than that using CMAX. The percentage is 9% at the condition of the average time of all nodes death. Therefore, UCLF is superior to CMAX in maximum lifetime. In the experiment, we observed such a phenomenon occurred in UCLF that with a decrease of nodes density in networks, lifetime of other nodes decreased rapidly. What causes this phenomenon is due to increase sharply energy consumption. As plenty of nodes died, the distribution of the clusters became sparse, therefore, communication routing between long distance nodes results a mass of energy consumption.

At last, the final effect picture of clustering is given by UCLF algorithm after a prolonged operation on the detail characterization of network simulation, as shown in Figure 14.

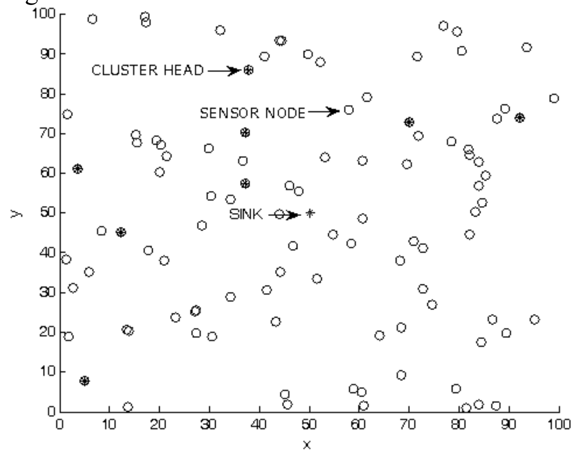

Figure 14. The final effect picture of clustering of UCLF

Ⅴ. CONCLUSIONS

We presented a new maximum lifetime routing algorithm based on uneven clustering, linear programming and fuzzy set theory. At first, the algorithm clustered WSN by using uneven clustering, then considers the fact that the maximum is taken over all optimized routing sequences whose link cost is a combination of the residual energy and the minimum energy at the nodes alive. In order to verify our assumptions about UCLF, we are currently extending the network simulator NS2 to simulate UCLF, comparing with CMAX. This will verify our assumptions and give us a more accurate picture of the advantages and disadvantages of the different protocols. Based on our NS2 simulations described above, the algorithm can alleviate the “hot spot” issues, and effectively extend the network lifetime.

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Jianhui Li was born in Yueyang, China, on August 21, 1974, received his B.S. degree in computer Science from Changsha Railway University, Changsha, China, in 1997, M.S. degree in soft engineering science from Hunan University, Changsha, China, in 2007. He is now a PhD student of Hunan Agricultural University, studying on WSN and crop informatics.

Guiping Liao was born in Shaoyang, China, on November 7, 1964, received his B.S. degree in agronomy from Hunan Agricultural College, Hengyang, in 1987, M.S. degree in Ecology from Chinese Academy of Sciences, Shenyang, China, in 1994, and PhD degree in agronomy from Hunan Agricultural University, Changsha, China, in 1999. He was a postdoctoral researcher on computer science and technology at National University of Defense Technology, from 2000-2003. He is currently a professor and PhD supervisor in College of Information Science and Technology, Hunan Agricultural University. His research interest includes Intelligent Information System, Virtual Plant and Computer Vision.

Fang Wang was born in Changsha of China, on June. 19, 1981. He graduated from Department of Mathematic, Huazhong University of Science and Technology, Wuhan, China, and worked at Science College, Hunan Agriculture University, Changsha, China. Fang received his Bachelor's degree from Department of Mathematics Hunan Normal University, Changsha, China. He received his Master's degree on mathematic from the Department of Mathematics, Huazhong University of Science and Technology，and he is pursuing his PhD degree in agricultural information institute in Hunan agriculture university. His major areas of research interests include image segmentation, image texture analysis and pattern recognition.

Jinwei Li was born in Anren, China, on September 27, 1974, received his B.S. degree in biology education from Xiangtan Normal University (Now: Hunan University of Science and Technology), Xiangtan, China, in 1997, M.S. degree in crop information science from Hunan Agricultural University, Changsha, China, in 2007. He received his PhD degree in crop informatics from Hunan Agricultural University. He is currently an assistant professor in College of Information Science and Technology, Hunan Agricultural University.