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Research Article

Fuzzy-Logic-Based Energy Optimized Routing for Wireless Sensor Networks

Haifeng Jiang,[1] Yanjing Sun,[2] Renke Sun,[1] and Hongli Xu[3]

[1] *School of Computer Science & Technology, China University of Mining and Technology, Xuzhou 221116, China*
[2] *School of Information & Electrical Engineering, China University of Mining and Technology, Xuzhou 221116, China*
[3] *Suzhou Institute for Advanced Study, University of Science and Technology of China, Suzhou 215123, China*

Correspondence should be addressed to Yanjing Sun; yanjingsun_cn@hotmail.com

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Wireless sensor nodes are usually powered by batteries and deployed in unmanned outdoors or dangerous regions. So, constrained energy is a prominent feature for wireless sensor networks. Since the radio transceiver typically consumes more energies than any other hardware component on a sensor node, it is of great importance to design energy optimized routing algorithm to prolong network lifetime. In this work, based on analysis of energy consumption for data transceiver, single-hop forwarding scheme is proved to consume less energy than multihop forwarding scheme within the communication range of the source sensor or a current forwarder, using free space energy consumption model. We adopt the social welfare function to predict inequality of residual energy of neighbors after selecting different next hop nodes. Based on energy inequality, the method is designed to compute the degree of energy balance. Parameters such as degree of closeness of node to the shortest path, degree of closeness of node to Sink, and degree of energy balance are put into fuzzy logic system. Fuzzy-logic-based energy optimized routing algorithm is proposed to achieve multiparameter, fuzzy routing decision. Simulation results show that the algorithm effectively extends the network lifetime and has achieved energy efficiency and energy balance together, compared with similar algorithms.

1. Introduction

Wireless sensor networks (WSNs) have emerged as an attractive technology for their wide range of applications in civil and military areas. In contrast to traditional wireless networks, wireless sensor nodes are usually powered by batteries and deployed in unmanned outdoors or dangerous regions [1, 2]. So, energy-constraint is a prominent feature for wireless sensor networks. Since the radio transceiver typically consumes more energy than any other hardware components onboard a sensor node, designing energy optimized routing algorithm is of great importance to prolong network lifetime [3].

Due to limited power on each sensor node, the routing algorithm should seek for energy efficiency and find less energy-consuming paths to transmit data. Intuitively, the network lifetime should be extended. However, most energy-efficient routing algorithms tend to route data via sensors on energy-efficient paths and thereby drain their energy quickly. For the ultimate goal of wireless sensor networks is to maximize network lifetime, significant efforts have been done to improve energy-efficient routing for the perspective of energy balance. In [4], single-hop or multihop forwarding scheme is selected to transmit data to Sink, according to the ability of sensor nodes. The direct transmission mode can save energy of the nodes closer to the Sink since their relaying burden can be relieved in this mode. EBDG [5] takes full advantage of corona-based network partition, mixed routing, and data aggregation to balance energy consumption. In [6], multipath mechanism is used to achieve energy balance. In [7], a proactive multipath routing algorithm is provided to achieve spatial energy balance, but it is actually a load balancing mechanism because of the assumption that "energy burden" and "traffic load" can be assimilated. However, it is not an optimal solution because spreading traffic unaware of residual energy distribution is somewhat blindfold. To balance the energy consumption in WSNs, residual energy scheming based energy equilibrium routing

protocol (RESEE) is proposed in [8]. In RESEE, a fuzzy gradient classification based next hop strategy has been designed to balance the energy consumption as a whole. In [9], using the variance of residual energy of sensors to measure the energy balance, predicting based distributed energy-balancing routing algorithm has been proposed. In [10], maximizing network lifetime by energy-aware routing has been formulated as integer programming problem, achieved energy efficiency as well as energy balance. But this algorithm has the central control architecture, and Sink needs to collect information of nodes and broadcast data transmission matrix to determine routes periodically, leading to heavy overhead of communication.

To prolong the lifetime of wireless sensor networks, the routing algorithm must be designed to achieve both energy efficiency and energy balance together. It should not only reduce the energy consumption for data transmission to extent the lifetime of a single node but also balance the energy consumption for the whole network. However, it is hard to optimize energy efficiency and energy balance simultaneously, which is difficult to be accurately described by mathematical model. How to realize the optimal combination of energy efficiency and energy balance is the key issue to extend the network lifetime. Fuzzy logic, on the other hand, has potential for dealing with conflicting situations and imprecision in data using heuristic human reasoning without needing complex mathematical model [11]. It is very well suited for implementing routing and clustering heuristics and optimizations, like link or cluster head (CH) quality classification [12, 13]. Judicious cluster head election can reduce the energy consumption and extend the network lifetime. A fuzzy logic approach based on energy, concentration, and centrality is proposed for cluster head election in [14]. This mechanism has some demerits that are caused by the centralized election mechanism. The Sink has to collect the energy and distance information from all sensor nodes. In [15], based on the improvement of the mechanism in [14], CHEF algorithm is proposed, which is a localized cluster head election mechanism using fuzzy logic. In [16], an energy-aware distributed dynamic clustering protocol (ECPF) is proposed, in which fuzzy logic is employed to assess the fitness (cost) of a node to become a CH. Both node degree and node centrality are taken into account to compute fuzzy cost. Simulation results show that ECPF provides superior network lifetime and energy savings than CHEF. In [17], a fuzzy-logic-based clustering approach with an extension to the energy predication has been proposed to prolong the lifetime of WSNs. In addition to the residual energy, the expected residual energy has been introduced to act as a fuzzy descriptor during the online CH selection process.

Although there are some researches using fuzzy logic to optimize cluster head election, but in the field of using fuzzy logic approach for flat routing has not been studied enough. In [11], the gateway is responsible for setting up of routes for sensor nodes and for the maintenance of centralized routing table that indicates the next hop for each sensor node. Gateway uses fuzzy logic to determine the cost of link between any two sensor nodes by input fuzzy variables, such as transmission energy, remaining energy, and queue size. Once the costs of all possible links to the gateway are computed, the route will be determined using the shortest path algorithm. But this approach is centralized, which is not suitable for the widely distributed WSNs. In [18], angle of placement and number of packets forwarded to the neighboring node are used as fuzzy system input parameters, and the node with greater chance is selected as next hop. In this method, the number of packets forwarded to neighboring nodes takes the place of the residual energy of nodes. But there are many packets sent from other nodes, so this replacement is not accurate.

The rest of this paper is organized as follows. Section 2 introduces the system model and defines data generation patterns. In Section 3, three energy optimized parameters are defined. A detailed description of fuzzy-logic-based energy optimized routing is given in Section 4. The simulation model and the comparative performance evaluation of the proposed routing algorithm are presented in Section 5. Section 6 concludes this paper.

2. System Model and Problem Specification

There are n homogenous sensor nodes randomly and uniformly distributed over a target area, and a Sink node collects events or sensed data from the sensors in each round. The primary design objective of the routing algorithm is to maximize the network lifetime. We clarify the problem by detailing energy consumption model and data generation patterns.

2.1. Energy Consumption Model. The energy consumption of each sensor node consists of three components: sensing energy, communication energy, and data processing energy. Sensing and data processing require much less energy than communication, so we consider only communication energy consumption. We use the same energy consumption model as Heinzelman used it for wireless communication hardware [19]. If the node transmits an l-bit packet over distance d, the consumed energy is

$$E_{\mathrm{Tx}}(l,d) = lE_{\mathrm{elec}} + l\varepsilon_{\mathrm{amp}}d^{\alpha}, \tag{1}$$

where E_{elec} denotes the energy/bit consumed by the transmitter electronics. $\varepsilon_{\mathrm{amp}}$ denotes the energy dissipated in the transmission amplifier and α represents the path loss exponent. The value of α is 2 for free space channel model and 4 for multipath fading channel model.

When receiving an l-bit packet, the energy consumption is

$$E_{\mathrm{Rx}}(l) = lE_{\mathrm{elec}}. \tag{2}$$

2.2. Data Generation Patterns. Many previous studies assume that each sensor has to send data to Sink in each round. That is, all sensors have a uniform data generation rate. However, in many applications, this assumption becomes unrealistic. In the case of forest fire detection, events can occur rarely and randomly over the target area. Therefore, the consideration of diverse potential data generation patterns is more reasonable.

For our work, three data generation patterns are considered as follows.

(i) Uniform data generation: every sensor transmits a data packet to the Sink in each round.

(ii) Random data generation: every sensor reports a data packet to the Sink with probability p in each round.

(iii) Data generation from a local area: only sensors in a local area have data to be transmitted to the Sink in each round. The shape of the area can be a circle, a square, or any other.

3. Energy Optimized Parameters

3.1. Degree of Closeness of Node to the Shortest Path. According to the energy consumption model of sensor nodes, the energy consumption for data transmission is proportional to the square of the distance between the source node and the destination for the free space model. If all relay nodes are on the line from data source node to the Sink, the whole energy consumption for data transmission would be minimized. So, the degree of closeness of node to the shortest path (DCSP) should be used as one of energy optimized parameters. Consider

$$\mathrm{DCSP}(k) = \frac{d(i, \mathrm{Sink})}{d(i,k) + d(k, \mathrm{Sink})}, \tag{3}$$

where i denotes source node and k denotes its forwarding node, whose distance to Sink is less than i. Note that DCSP(k) attains its maximum (DCSP(k) = 1) when k lies on the line from i to Sink. The intuition behind the concept of DCSP is to make the data forwarding path not to deviate much from the shortest path between the current sender (i.e., the source of the data or any current forwarder) and the Sink.

3.2. Degree of Closeness of Node to Sink. In the process of data transmission, two data forwarding schemes: single-hop or multihop can be used within the communication range of the current sender. A forwarding scheme is said to be single-hop if each sensor in a data forwarding path can use at most one of its one-hop neighbors to forward a data packet toward its ultimate destination. A forwarding scheme is said to be multihop if the same data is forwarded through multiple neighbors of each sensor until the data reaches its destination. As can be seen from Figure 1, sensor i can send data to sensor j directly (single-hop) or through a relay node k (multihop). These two forwarding schemes consume different amounts of energy, which will be analyzed as follows.

Let us compute the energy consumption for sending data from sensor i to j using the previously mentioned two forwarding schemes for the free space model. Let

$$\begin{aligned} E_{\text{single-hop}} &= 2lE_{\text{elec}} + l\varepsilon_{\text{amp}} d^2(i,j), \\ E_{\text{multihop}} &= 4lE_{\text{elec}} + l\varepsilon_{\text{amp}} \left(d^2(i,k) + d^2(k,j)\right) \end{aligned} \tag{4}$$

be the energy consumption required to forward data from sensor i to j through single-hop and multihop forwarding schemes, respectively.

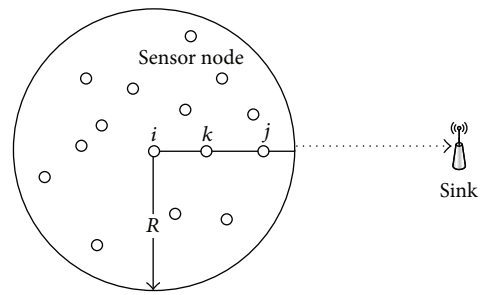

Figure 1: Data transmission in one-hop region.

Assume that sensor k lies on the line segment (i, j); that is, $d(i, j) = d(i, k) + d(k, j)$. If multihop short-range forwarding scheme is more energy efficient than single-hop, it implies $E_{\text{single-hop}} > E_{\text{multihop}}$. From (4), we can drive

$$d(i,k) \times d(k,j) > \frac{E_{\text{elec}}}{\varepsilon_{\text{amp}}}. \tag{5}$$

If sensor k is not on the line segment (i, j), we can drive

$$d^2(i,j) - d^2(i,k) - d^2(k,j) > \frac{2E_{\text{elec}}}{\varepsilon_{\text{amp}}}. \tag{6}$$

In this paper, we use the same parameter values for wireless communication hardware as Heinzelman used them in [19]. The numerical values of some parameters are as follows: $R = 30\,\text{m}$, $E_{\text{elec}} = 50\,\text{nJ/bit}$, and $\varepsilon_{\text{amp}} = 10\,\text{pJ/bit/m}^2$. It is easy to check that (5) and (6) are not established. So, single-hop forwarding scheme is more energy efficient within the one-hop communication range of the source sensor or a current forwarder. In order to save energy, the neighbor node which is more close to Sink should be selected as next hop. The definition of degree of closeness of node to Sink (DCS) is

$$\mathrm{DCS}(k) = \frac{1/d(k, \mathrm{Sink})}{\sum_{j \in \mathrm{FN}(i)} 1/d(j, \mathrm{Sink})}, \tag{7}$$

where $d(k, \text{Sink})$ represents distance from node k to Sink and FN(i) denotes the forwarding neighbor set of source node i.

3.3. Degree of Energy Balance. The existing energy-balancing routing algorithms are generally based on the residual energy of sensors to transform the selection of next hop, which is a kind of passive method of routing decision. When the data forwarding path is updated, the inequality of residual energy of sensors has already emerged. In our study, we adopt initiative routing adjustment strategy to predict the inequality of residual energy when selecting different forwarding neighbors as next hop and selecting the one with the highest degree of energy balance as next hop. In social sciences, there have been considerable efforts to define the so-called social welfare function to compare income welfare between space and time. In general, social welfare is a function of average and equality of an income population. In this paper, the energy unbalance

(EUB) of s set of sensors is computed using Atkinson welfare function according to [20]

$$\mathrm{EUB} = 1 - \left[\frac{1}{n} \sum_{i \in A} \left(\frac{E(i)}{\overline{E}} \right)^{1-\varepsilon} \right]^{1/(1-\varepsilon)} \tag{8}$$

EUB denotes energy unbalance of sensors in one-hop communication region A and n is the number of sensors in this region. $E(i)$ denotes the residual energy of sensor i and $\overline{E}$ the average residual energy. ε denotes the inequality aversion index, which takes values ranging from zero to infinity. The values of ε that are typically used include 1.5, 2.0, and 2.5.

To evaluate the alternative next hop, the sensor i calculates expected EUB of its local society consisting of its forwarding neighbors and itself according to the estimated residual energy of these sensors. After computing EUB for each alternative next hop, the forwarding neighbor is selected if the node gives the minimum EUB.

On the assumption that forwarding node k is selected as the next hop and the data is transmitted to it, the expected residual energy of sensor i is

$$E^{ik}(i) = E(i) - E_{\mathrm{Tx}}(l, d(i,k)). \tag{9}$$

The expected residual energy of sensor k after receiving and transmitting the same data (transmission distance approximates to R) is

$$E^{ik}(k) = E(k) - E_{\mathrm{Rx}}(l) - E_{\mathrm{Tx}}(l, R). \tag{10}$$

There is no change on residual energy of other neighbors not involved in data transmission, which is shown as

$$E^{ik}(j) = E(j). \tag{11}$$

Using the expected residual energy from (9), (10), and (11), sensor i can calculate the expected EUB for each decision k by (12), which is based on the Atkinson welfare function

$$\mathrm{EUB}^{ik} = 1 - \left[\frac{1}{n} \sum_{j \in N(i)+\{i\}} \left(\frac{E^{ik}(j)}{\overline{E^{ik}}} \right)^{1-\varepsilon} \right]^{1/(1-\varepsilon)}, \tag{12}$$

where

$$\overline{E^{ik}} = \frac{1}{n} \sum_{j \in N(i)+\{i\}} E^{ik}(j). \tag{13}$$

After sensor i has calculated EUB for each forwarding neighbor, the degree of energy balance (DEB) for selecting node k as next hop is calculated by

$$\mathrm{DEB}(k) = \frac{1/\mathrm{EUB}^{ik}}{\sum_{j \in \mathrm{FN}(i)} 1/\mathrm{EUB}^{ij}}. \tag{14}$$

4. Fuzzy-Logic-Based Routing

Fuzzy logic is used in this work as main implementation of perceptive reasoning. A fuzzy system basically consists of three parts: fuzzifier, fuzzy inference engine, and defuzzifier. The fuzzifier maps each crisp input value to the corresponding fuzzy sets and thus assigns it a truth value or degree of membership for each fuzzy set. The fuzzified values are processed by the inference engine, which consists of a rule base and various methods for inferring the rules. The rule base is simply a series of IF-THEN rules that relate the input fuzzy variables with the output fuzzy variables using linguistic variables, each of which is described by a fuzzy set. The defuzzifier performs defuzzification on the fuzzy solution space. That is, it finds a single crisp output value from the solution fuzzy space.

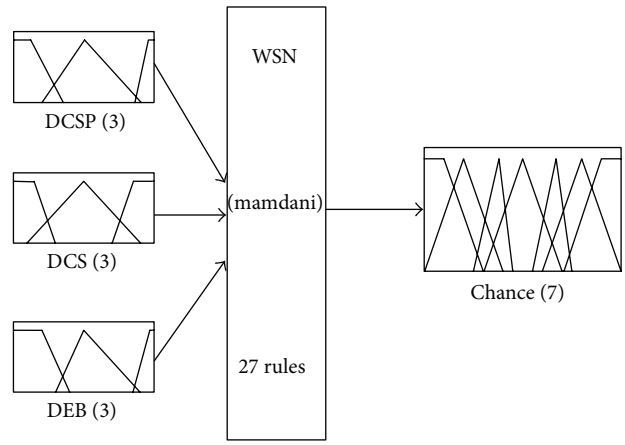

Figure 2: Model of fuzzy system.

The objective of our fuzzy-logic-based routing is to determine the energy optimized routing based on the parameters defined previously, such that the network lifetime is maximized. The fuzzy rule base has been tuned so as not only to minimize energy consumption but also to balance data traffic among sensor nodes effectively.

Figure 2 gives our fuzzy system model. Mamdani algorithm is used to realize fuzzy logic inference. The input fuzzy variables are degree of closeness of node to the shortest path (DCSP), degree of closeness of node to Sink (DCS), and degree of energy balance (DEB). The first two variables reflect the measure of energy efficiency for selecting one node as next hop, and the last variable shows the measure of energy balance for routing decision. The rule base consists of 27 (3^3) rules. There is a single output fuzzy variable, namely, chance, the defuzzified value of which determines the chance for one forwarding neighbor which has been selected as next hop.

Figure 3 displays details of the input and output fuzzy variables. The linguistic variables, used to represent DCSP and DCS, are divided into three levels: far, medium, and close, respectively, and there are three levels to represent DEB: poor, medium, and good, respectively. The output fuzzy variable to represent the node next hop election chance is divided into seven levels, which are very small, small, rather small, medium, rather large, large, and very large. The fuzzy rule base currently includes rules like the following: if DEB is good, DCSP is close, and DCS is close, the chance of the node to be selected as next hop is very large. The forwarding

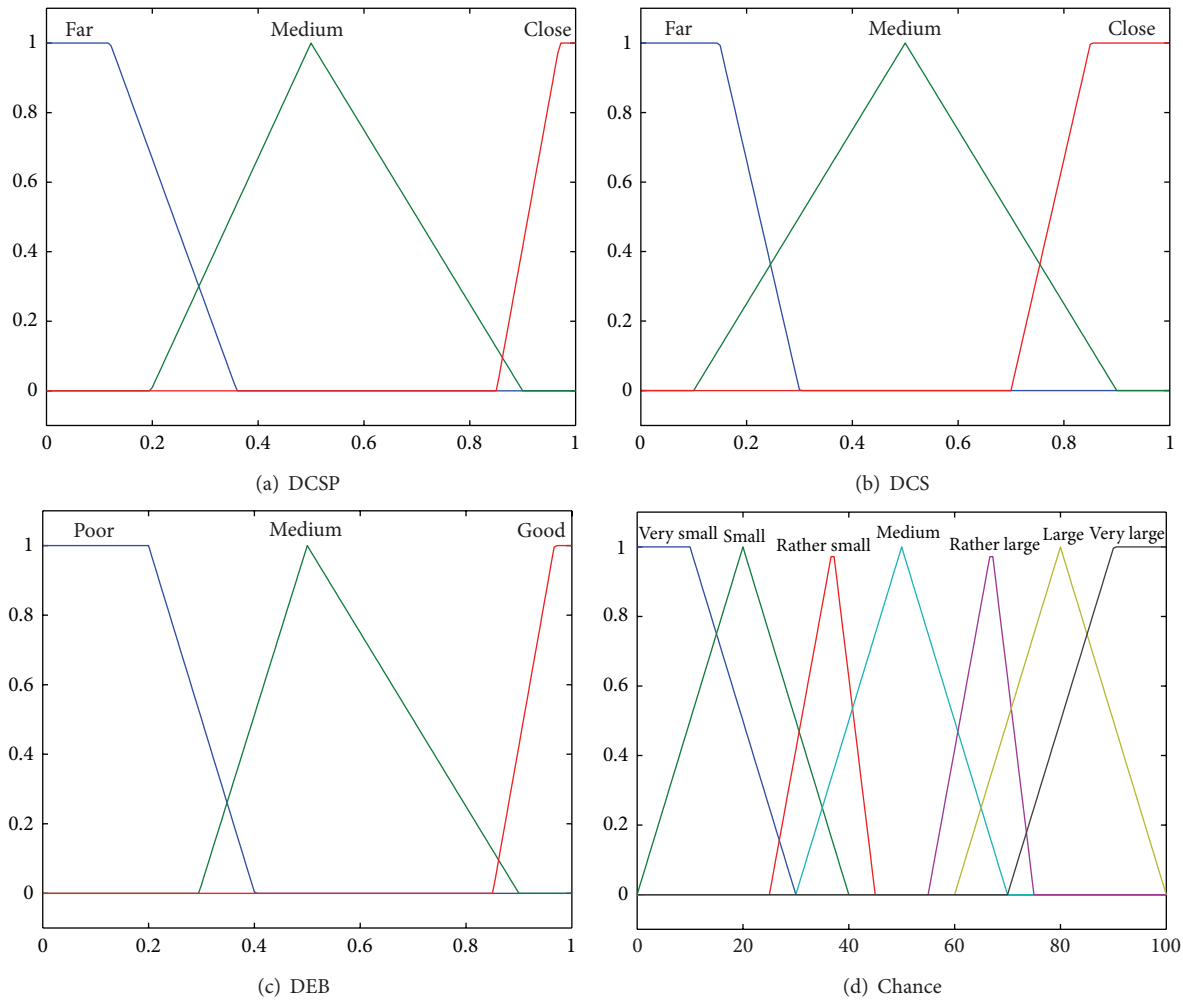

Figure 3: Fuzzy membership functions of input and output variables.

neighbors of the source sensor or a current forwarder are compared on the basis of chances, and the node with the maximum chance is then selected as the next forwarder. Mathematically, the crisp output domain value *chance*, from solution fuzzy region A, is given by

$$\text{Chance} = \frac{\sum_{i=1}^{27} W_i \mu_A(W_i)}{\sum_{i=1}^{27} \mu_A(W_i)}, \tag{15}$$

where W_i is the domain value corresponding to rule i and $\mu_A(W_i)$ is the predicate truth for that domain value.

5. Results and Discussion

In this section, we evaluate the performance of our proposed fuzzy-logic-based energy optimized routing (FLEOR) algorithm via MATLAB. We calculate the energy consumption for data transmission and reception. We define the network lifetime as the time when the residual energy of the first sensor node becomes zero, which is counted by round. We compare the performance of FLEOR algorithm with a predicting based distributed energy-balancing routing (PDEBR) [9], minimum transmission energy (MTE) routing [21], greedy perimeter stateless routing (GPSR) [22], and energy accounted minimum hop routing (EAMHR) [23] on the network lifetime, energy balance, and energy efficiency. In our simulations, sensor nodes are randomly and uniformly deployed over the square monitoring area. The Sink is placed at the outside of the monitoring area. Other simulation parameters are given in Table 1.

5.1. Network Lifetime. Figures 4, 5, and 6 give the network lifetime under different data generation patterns: uniform, random, and specific local area, respectively, when the number of sensors increases from 50 to 200. In our simulations, the data generation rate is set to be 0.25 for the random data generation pattern, which means that sensors generate data with probability of 0.25 in each round, while, for pattern of data generation from a local area, sensors located in a square area from (0, 0) to (50, 50) send data repeatedly.

As shown in Figure 4, FLEOR algorithm has extended the network lifetime under uniform data generation pattern, compared with PDEBR, EAMHR, GPSR, and MTE algorithms. GPSR and MTE algorithms make routing decisions

Table 1: Simulation parameters.

Parameter	Value
Network coverage/m^2	100×100
Number of sensors	50~200
Sink coordinates	(50, 110)
Initial energy/J	0.5
E_{elec}/(nJ·bit^{-1})	50
ε_{amp}/(pJ·bit^{-1}·m^{-2})	10
Data packet size/B	500
Control packet size/B	12
ε	2.5
Maximum transmission range/m	30

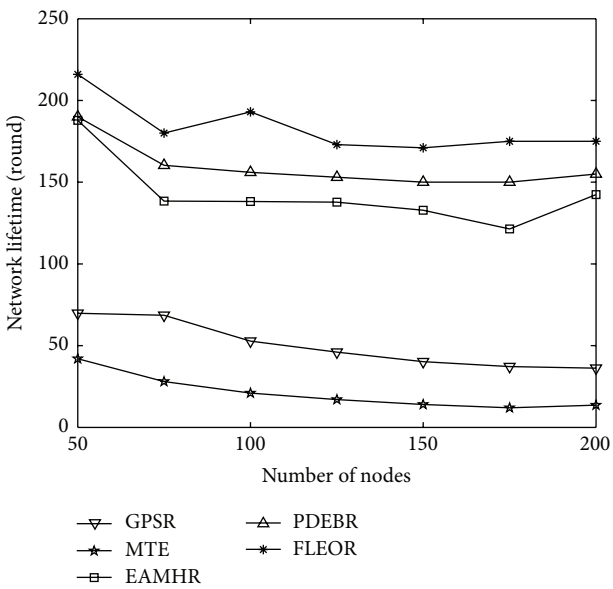

Figure 4: Network lifetime under uniform data generation pattern.

based on the location of neighbors and have no attempt on energy balance, resulting in short network lifetime. The node closest to Sink especially in MTE will relay the data of the whole network, resulting in quick energy consumption and the shortest network lifetime. EAMHR selects the node with the most residual energy as next hop from forwarding neighbors, which has achieved combination of energy efficiency and energy balance to a certain extent and prolonged network lifetime compared with GPSR and MTE. PDEBR predicts mean square deviation of residual energy of neighbors and selects the node with the minimum value as next hop from front neighbors. It has achieved the distributed local energy balance and has longer network lifetime compared with EAMHR, GPSR, and MTE. FLEOR combines energy efficiency and energy balance together through fuzzy logic. Compared with PDEBR and EAMHR, FLEOR has extended network lifetime further, which means that FLEOR can achieve a better combination of energy efficiency and energy balance.

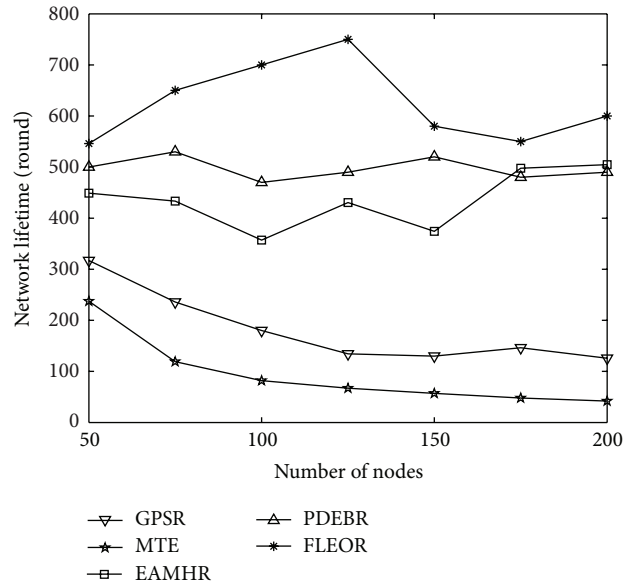

Figure 5: Network lifetime under random data generation pattern.

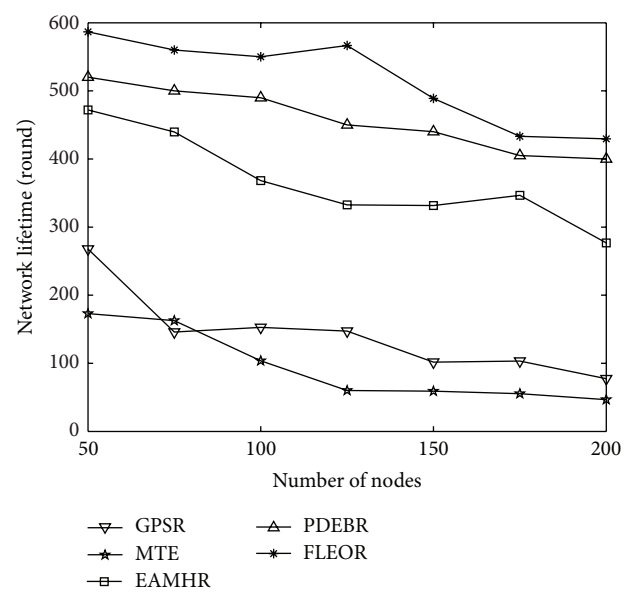

Figure 6: Network lifetime under data generation pattern from a local area.

Figures 5 and 6 show that FLEOR has significant advantages on network lifetime under random data generation pattern and local area data generation pattern, compared with other algorithms. With these results, we can say that FLEOR is adaptable to different data generation patterns and is more suitable for real network design requirements.

5.2. Energy Balance and Energy Efficiency. Figure 7 gives the average residual energy of nodes under uniform data generation pattern when the first node becomes incapacitated. In GPSR and MTE, there is no consideration on energy balance for routing decision. So, there are many nodes with more

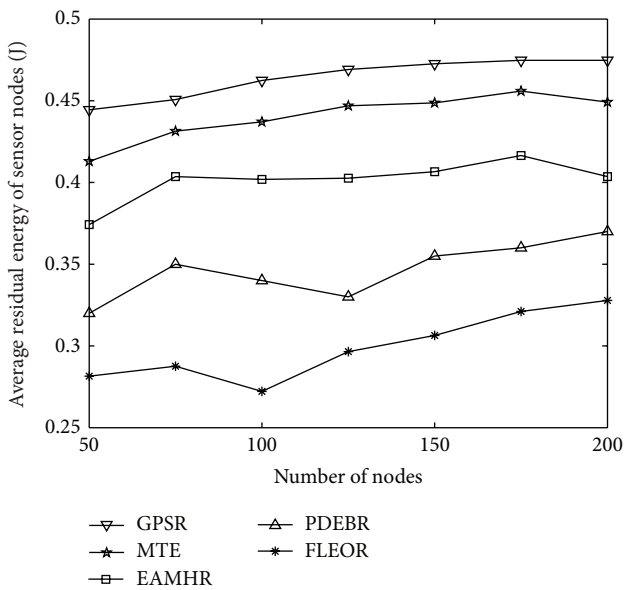

Figure 7: Average residual energy of sensor nodes.

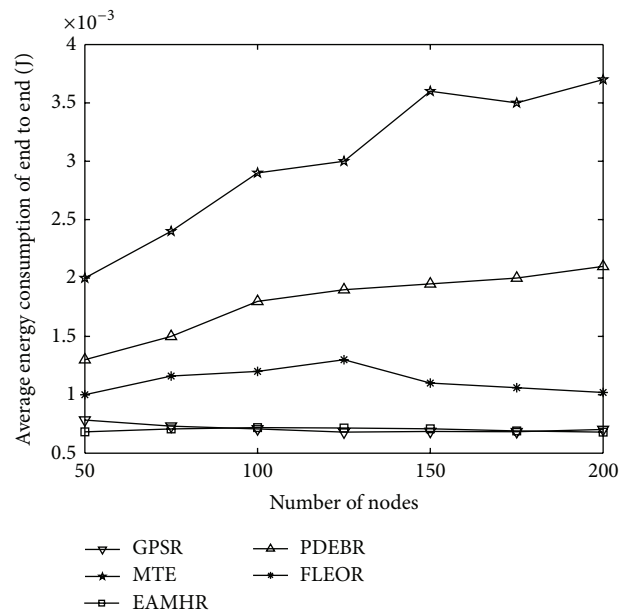

Figure 8: Average energy consumption of end to end.

residual energy when the first node becomes incapacitated, compared with FLEOR, PDEBR, and EAMHR.

Figure 8 gives the average energy consumption of end to end for different algorithms under uniform data generation pattern. From this figure, we can see that the average energy consumption of end to end in GPSR and EAMHR is close and maintained at a low level, which shows a good performance on energy efficiency. In PDEBR, the node with the minimum predicted mean square deviation of residual energy is selected as next hop, although it is near the sending node and far from the Sink. So, the average energy consumption of end to end in PDEBR is larger than GPSR, MTE, and FLEOR. In MTE, the multihop short-range forwarding scheme is used to transmit data, which has been proved to be less energy efficient within the communication range of the current forwarder. So, the average energy consumption of end to end in MTE is the most and shows the upward trend with the increase of network size. In FLEOR, the energy balance of nodes is considered preferentially when making routing decisions. As a result, the average energy consumption of end to end in FLEOR is higher than GPSR and EAMHR. At the same time, FLEOR has achieved energy efficiency, leading to less average energy consumption of end to end and restraint of its rising trend with the increase of the number of nodes, compared with MTE and PDEBR.

6. Conclusions

In this paper, we have designed three energy optimized parameters, such as the degree of closeness of node to the shortest path, degree of closeness of node to Sink, and degree of energy balance, and put these parameters into fuzzy logic system. The fuzzy-logic-based routing algorithm is proposed to realize energy optimized, multiparameter, and fuzzy routing decision. Simulation results show that the algorithm extends the network lifetime effectively compared with similar algorithms for different dada generation patterns and has a good performance in terms of energy balance and energy efficiency.

Our future work will focus on the applications for multimedia. While achieving optimized energy consumption of the whole network, the Qos, such as bandwidth, latency, and packet loss rate will be considered to meet the requirements of specific applications.

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