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Energy-balance node-selection algorithm for heterogeneous wireless sensor networks

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To solve the problem of unbalanced loads and the short network lifetime of heterogeneous wireless sensor networks, this paper proposes a node-selection algorithm based on energy balance and dynamic adjustment. The spacing and energy of the nodes are calculated according to the proximity to the network nodes and the characteristics of the link structure. The direction factor and the energy-adjustment factor are introduced to optimize the node-selection probability in order to realize the dynamic selection of network nodes. On this basis, the target path is selected by the relevance of the nodes, and nodes with insufficient energy values are excluded in real time by the establishment of the node-selection mechanism, which guarantees the normal operation of the network and a balanced energy consumption. Simulation results show that this algorithm can effectively extend the network lifetime, and it has better stability, higher accuracy, and an enhanced data-receiving rate in sufficient time.

KEYWORDS
direction factor, heterogeneous wireless sensor networks, link, load balancing, network life, node

1 | INTRODUCTION

With the rapid development of wireless communication technology, wireless sensor networks (WSNs) have been widely used in numerous applications, such as environmental monitoring, medical treatment, industrial automation, smart home development, military, and the Internet of Things (IoT) [1–3]. In WSNs, nodes are usually randomly broadcasted or manually placed around the perceptual object in order to achieve the target perception data collection and forwarding. Complex and heterogeneous networks can be modeled using epidemic spreading [4], the epidemic process of complex and heterogeneous connectivity patterns [5], and non-Markovian social contagion models [6]. Depending on the sensor node structure, there are two kinds of sensor network, namely isomorphic networks and heterogeneous networks [7,8]. As isomorphic networks are composed of low-cost nodes that have the same structure and which are easily deployed, they often encounter problems such as a generally low network energy utilization rate and an unbalanced energy consumption of nodes, leading to premature node death and long-term network failure [9]. Therefore, this study focuses on heterogeneous networks.

In the existing research on heterogeneous networks, there are fewer works on network equilibrium compared with homogeneous networks. In [10], a node-protection mechanism is proposed to reduce the influence of the environment on nodes and to improve the node's data transmission accuracy. However, the network energy balance cannot be guaranteed. Reference [11] proposed a multiattribute routing mechanism to reduce the use of unnecessary resources in the network and to prevent network redundancy. However, it is easy for some network nodes to consume too much energy. Reference [12] proposed a random-walk-based heterogeneous network node sorting algorithm that uses the similarity between nodes, and

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which effectively improves the data transmission accuracy. However, it cannot guarantee the service life of the network. The above algorithms optimize the network by adopting the node-protection mechanism and the sorting algorithm, which can effectively improve the data transmission accuracy of the network. However, the energy consumption and the balance of the network continue to exhibit excessive energy consumption and imbalance.

In view of the above problems, this paper analyses WSN nodes on the basis of the selection probabilities and energy balance of node paths for which a novel node-selection algorithm for transmission energy-balance optimization is proposed. First, to determine the energy of the network nodes, the maximum distance and the energy that is transmitted and received by the network nodes are obtained in advance. Then, considering the shortages of the existing path-selection probabilities, direction and energy-adjustment factors are introduced to optimize the choice of path node. Finally, a node-filtering mechanism is established to remove the path in the energy-insufficient nodes in order to realize the dynamic selection and energy balance of network nodes. In addition, the stability and accuracy of the proposed algorithm are verified by performing data analyses in MATLAB, and it was proven that the algorithm can prolong the network lifetime under different energy environments.

2 | SYSTEM ANALYSIS

2.1 | Network model

Suppose there are N nodes in the heterogeneous network. E_0 is the initial energy value of nodes, and is randomly distributed in the area on $M \times N$, as shown in Figure 1. Nodes in a heterogeneous network satisfy the following conditions [13,14]:

A. The total energy value of the network when constructing the initial energy of the node is fixed.
B. Nodes can get their own coordinate information. At the same time, they can also communicate with each other in the communication range to obtain the distance between each other.
C. The initial energy of each node in the network is the same.
D. Each node works independently.

An undirected graph $G = (V, L)$ can be used in the network topology, where V represents the set of nodes and L represents the node's link set. Suppose that node i can receive the signal sent by node j. Then, the distance between node i and j is $d(i, j)$, where node j is adjacent to node i, where there are other nodes within the valid range of node i, which together constitute the neighbor set of node i. In addition, the adjacent nodes that make up the link are within the range of two nodes that receive and send data between themselves. The schematic diagrams of the adjacent node and link node are shown in Figures 2 and 3, respectively.

2.2 | Node probability model

According to the above network, node distribution in the heterogeneous network, the probability of each node in the network is closely related to the distance and direction between the nodes [15]. For the link to be formed, the two nodes should be within the effective distance of one data exchange. Therefore, assuming that the sending node is i and the receiving node is j, the generation probability of i to j is:

$$P_{ij} = \mathrm{e}^{-R_{\mathrm{tx}}|\sin\theta|} \tag{1}$$

where R_{tx} is the sending effective distance between node i and j; θ is the direction of nodes i and j. The probability of undetected nodes at this time can be approximately defined as:

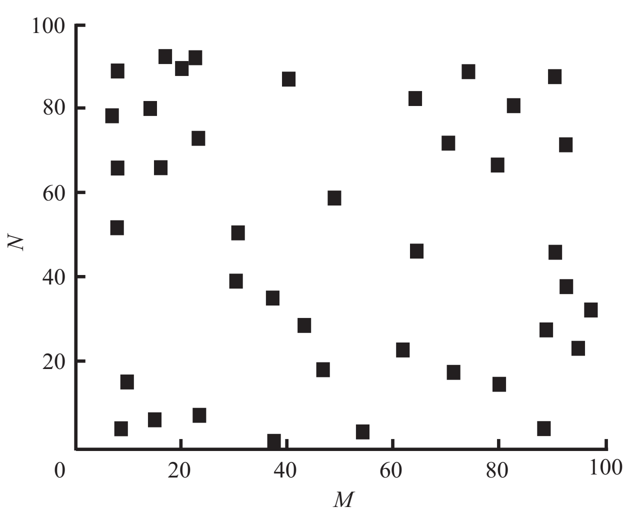

FIGURE 1 Node distribution in heterogeneous network

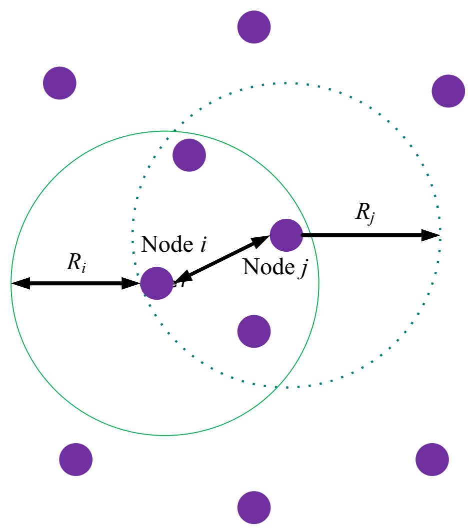

FIGURE 2 Illustration of an adjacent node in the proposed system

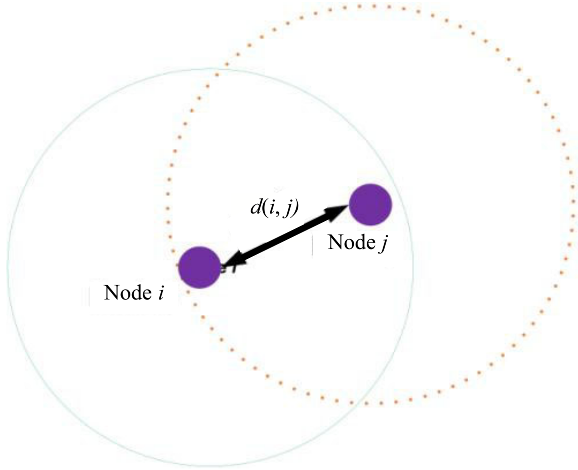

FIGURE 3 Illustration of a link node in the proposed system

$$\tilde{P}_{ij} = 1 - P_{ij}. \quad (2)$$

The probability that node j cannot be detected by all nodes is:

$$\tilde{P} = \prod_{i=1}^{N} (1 - P_{ij}) \leq \Omega \quad (3)$$

where $0 < \Omega < 1$ is the probability constraint value.

3 | PROBLEM ANALYSIS

By analyzing the network model of heterogeneous networks and the probabilistic model, it was determined that the network data transmission effect is closely related to the network node. However, in order to effectively improve the network equalization and lifetime, many researchers have proposed only the node-selection mechanism, while ignoring the following three kinds of problems that exist between the nodes:

1) According to the node probability equation, the probability of a node is related to the distance and direction of the network node. However, the traditional algorithm only considers the transmission distance, and neglects the receiving distance of the node when calculating the distance between nodes; this will undoubtedly produce data transmission errors.
2) The signal in the network is not always the same for all transmission distances from the node. However, when the path length is too great, there will be fading, thereby reducing the effective data transfer rate.
3) The energy of the network node is limited, and the extent of its reception and transmission capacity depends on the node energy. When the energy is insufficient, if the node is not replaced in time, it will result in the loss of network data.

The above problems directly affect the data transmission of the entire network. Therefore, this paper proposes a novel algorithm to optimize such problems using the node probability, signal, and energy optimization.

4 | PROPOSED ALGORITHM

4.1 | Node transmission distance calculation

By studying the above network model, it can be determine that in order to realize mutual communication between network links, it is necessary to detect each other within the transmission distance of the network node and the carrier sense distance [16,17]. To calculate the transmission distance of each node, we need to calculate the maximum range of the generating node and receiving node. To this end, we convert the problem of seeking the node-transmission distance into the maximum transmission distance and the maximum receiving distance of the node, as follows:

Let the maximum radius that can be successfully received in the ideal state be the node's transmission distance, R_{tx}. The receiving effect of nodes and the distance between nodes are considered. Therefore, its function expression is defined as:

$$R_{\text{tx}} = d_0 \times \frac{1}{\alpha} \left(\frac{P_0}{\text{RX}_{\text{thresh}}} \right) \quad (4)$$

where d_0 denotes the reference distance ($d_0 \neq 0$), P_0 denotes the received power at the reference distance, $\text{RX}_{\text{thresh}}$ denotes the received power threshold, and α denotes the power loss index, where $\alpha > 1$.

At the sending end, suppose the node can detect the maximum transmission radius, that is, the carrier-sensing distance is R_{cs}. Then, the expression is:

$$R_{\text{cs}} = d_0 \times \frac{1}{\alpha} \left(\frac{P_0}{\text{CS}_{\text{thresh}}} \right) = \frac{1}{\alpha} \left(\frac{\text{RX}_{\text{thresh}}}{\text{CS}_{\text{thresh}}} \right) \times R_{\text{tx}} = \Delta_s \times R_{\text{tx}} \quad (5)$$

where $\text{CS}_{\text{thresh}}$ is the carrier-sensing threshold, and $R_{\text{tx}} > \text{CS}_{\text{thresh}}$; Δ_s takes the value of 1.2.

4.2 | Node energy calculation

In this paper, the node energy is defined according to the distance and energy consumption characteristics of nodes. Depending on the fading relationship of the signal, the energy is calculated according to (4) and (5).

The energy function of the sending node is:

$$E_{\mathrm{tx}}(i) = \begin{cases} \eta.E_{\mathrm{elec}} + \eta.\varepsilon_{\mathrm{fs}} d^2, & d < R_{\mathrm{tx}} \\ \eta.E_{\mathrm{elec}} + \eta.\varepsilon_{\mathrm{mp}} d^4, & d \geq R_{\mathrm{tx}} \end{cases} \tag{6}$$

where η is the number of bits used for transmitting information, d is the distance to the current node, E_{elec} is the energy consumption required to send and receive each bit of data, $\varepsilon_{\mathrm{fs}}$ is the free-space power amplification energy consumption coefficient, and $\varepsilon_{\mathrm{mp}}$ is the multipath fading power amplification energy consumption coefficient.

For the receiving node, there is no need to consider the node's free-space power. Therefore, the available energy function of the receiving node is:

$$E_{\mathrm{es}}(i) = \begin{cases} \eta.E_{\mathrm{elsc}}, & d < R_{\mathrm{cs}} \\ \eta.\frac{E_{\mathrm{elsc}}}{d}, & d \geq R_{\mathrm{cs}} \end{cases} \tag{7}$$

where the transmission energy consumption is mainly the energy consumed during the signal processing and power amplification.

4.3 | Dynamic node probability

In wireless communication networks, especially in heterogeneous sensor networks, the node energy is not static, and decreases gradually with time [18,19]. Therefore, if we randomly choose a fixed probability value to represent the roaming probability between nodes, it will undoubtedly deviate from the calculations of the network. The initial phase of heterogeneous network nodes requires a greater energy charge. However, with the extension of the network usage time, the energy of the nodes in the network will gradually be utilized, and there will be the problem of insufficient remaining energy. In this paper, the node-selection probability is further optimized by setting the network energy-adjustment factor δ, as well as establishing a reasonable reward and punishment mechanism to enhance and weaken the probability.

The reward and punishment mechanism is described as follows:

In the case of nodes with abundant energy, that is, $E_i > E_{i\,\mathrm{min}}$ the probability is improved, and the function expression is:

$$P'_{ij} = \delta \times P_{ij} \times e^{-\frac{E_i}{E_0}} \times \frac{E_i}{E_0}. \tag{8}$$

In the case of lack of energy in the node, that is, $E_i < E_{i\,\mathrm{min}}$ the probability is weakened, and the function expression is:

$$P'_{ij} = \delta \times P_{ij} \times e^{-\frac{E_i}{E_0}} \times \frac{E_{i\,\mathrm{min}}}{E_i} \tag{9}$$

where δ is the energy-adjustment factor of the network, E_0 is the initial energy value of node i, $E_{i\,\mathrm{min}}$ is the minimum energy value of the node. That is, it can only support the remaining energy of a signal's sending or receiving action of the node. The function expression is:

$$E_{i\,\mathrm{min}} = \frac{k \times \min\{E_{\mathrm{tx}}(i), E_{\mathrm{es}}(i)\}}{N} \tag{10}$$

where N is the total number of network nodes, k is the number of nodes in the receiving range, and $\min\{E_{\mathrm{tx}}(i), E_{\mathrm{es}}(i)\}$ is the minimum of $E_{\mathrm{tx}}(i)$ and $E_{\mathrm{es}}(i)$, respectively.

In this study, by introducing the network energy-adjustment factor, the network size is reduced. However, in order to achieve the network node-load balancing and energy-efficient utilization, the energy of the nodes is sufficiently enhanced to ensure that the network-receiving domain energy is balanced.

4.4 | Path selection

Meta-path eigenvalues for network G <U, L, E, W> are given. The path between path P and its instance is P'. The path of path P is the sum of the degree of association represented by all path instances [20]. The formula is:

$$\mathrm{Eip}(P) = \sum_{p \in P'} \mathrm{cor}(p) \tag{11}$$

where $\mathrm{cor}(p)$ for the instance path p reflects the degree of the internode association. The example path $p = (a_1, a_2, a_3, \ldots, a_n)$, where a_i is the network node and a_i ε L is the node of interest. In this paper, $\mathrm{cor}(p)$ is calculated by random walk, as follows:

Suppose a particle departs from node a_1 and travels randomly through the network. At this point, $\mathrm{cor}(p)$ is the probability of the particle traveling to a node in accordance with the instance p. Among them, the probability of each run-off is equal to the probability of events, and the independent completion of the particle can be used to calculate the probability of walking in accordance with the example path p.

$$\mathrm{cor}(p) = \prod_{i=1}^{n} P'_{ij}. \tag{12}$$

Here, P'_{ij} represents the walking probability between node i and node j in the random-walk process.

4.5 | Path node-filtering mechanism

To calculate the interest nodes, this paper optimizes the probability using the path-selection mechanism mentioned above. However, in order to improve the utilization rate of network path nodes, a node-selection mechanism Rotation (i, r) is also introduced. By combining the node probability and energy consumption, the path node is selected, and the function expression is as follows:

$$\text{Rotation}(i,r) = \frac{1}{P'_{ij}} - \frac{\Delta E}{P'_{ij}} = (1-\Delta E)\frac{1}{P'_{ij}} \tag{13}$$

where i represents node i, r is the usage period of node i, and ΔE is the energy consumption factor, which satisfies the following formula:

$$\Delta E = \begin{cases} 0, & E(i,r)_{\text{remin}} > E_{i\ \min} \\ \frac{E_0 - E(i,r)_{\text{remin}}}{\frac{1}{N}\sum_{i=1}^{N}(E_0 - E(i,r)_{\text{remin}})}, & E(i,r)_{\text{remin}} < E_{i\ \min} \end{cases} \tag{14}$$

where $E(i,r)_{\text{remin}}$ indicates the remaining minimum energy of the node value. When $E(i,r)_{\text{remin}} > E_{i\min}$, then the node energy at this time is high, and it can be approximately defined as $\Delta E = 0$. When $E(i,r)_{\text{remin}} < E_{i\min}$, it indicates that the node starts to lack energy. In this case, the value of ΔE increases, which helps to eliminate nodes with insufficient energy. If $\text{Rotation}(i,r) > 0$, node i advances $\text{Rotation}(i,r)$ round to set G. If $\text{Rotation}(i,r) = 0$, the current rotation does not change. If $\text{Rotation}(i,r) < 0$, the node delays the $|\text{Rotation}(i,r)|$ into set G in order to achieve the dynamic node.

This study uses the above node-filtering mechanism to dynamically mobilize the nodes in the network and eliminate the network nodes with insufficient energy in real time so as to ensure the normal balance between the network and the energy consumption.

4.6 | Algorithm flow

The specific steps of this algorithm are as follows:

Algorithm 1. Proposed EBDA Algorithm

1: Initialize the network.

2: Convert the transmission distance to R_{cs} and R_{tx} of the node.

3: Calculate $E_{tx}(i)$ of the node by using (4) and (5).

4: Determine the node probability using δ and combine with step 3 to reduce the probability that network energy-deficient nodes are selected, and also enhance the abundant node energy.

5: Calculate probability cor(p).

6: Filter nodes via Rotation(i,r).

5 | SIMULATION RESULTS

In order to verify the feasibility of this algorithm, MATLAB is used to carry out the simulation analysis. Assuming that 100 nodes are distributed over a 100 m × 100 m area, the nodes in the network are randomly distributed. The experimental parameters used in the simulation are shown in Table 1.

Under the condition that the nodes satisfy the distribution of the above heterogeneous networks, the simulation results obtained by this algorithm are compared with the traditional path-selection algorithm and the algorithm in [21] to verify the performance of the proposed algorithm.

TABLE 1 Simulation parameters

S. No	Parameter	Expression	Value
1	Power amplifier energy consumption	$\frac{\varepsilon_{fs}}{(pJ.bit^{-1}.m^{-2})}$	10
2	Multipath fading power amplification energy consumption	$\frac{\varepsilon_{mp}}{(pJ.bit^{-1}.m^{-4})}$	0.0013
3	Energy consumption of each node's initial data	$\frac{E_{elec}}{(nJ.bit^{-1})}$	50
4	Reference distance between nodes	$\frac{d_0}{m}$	30

To compare the performance of the algorithm more intuitively, the network life contrast experiment, stability experiment, network accuracy, and data reception were compared, and the data were obtained using the visualization of the graph.

5.1 | Network life comparison

By setting different initial energy values for the network, in order to compare the balance of the system, the number of nodes was compared with the length of the network lifetime of the system, which was obtained by adopting the above algorithm. Therefore, in this study, two kinds of initial network energy values, which have different magnitudes, were considered, that is, 10 J and 50 J, respectively. The network lifetime curve after the simulation is shown in Figures 4 and 5.

It can be seen that the proposed algorithm has a higher network lifetime in both lower and higher initial energy, as

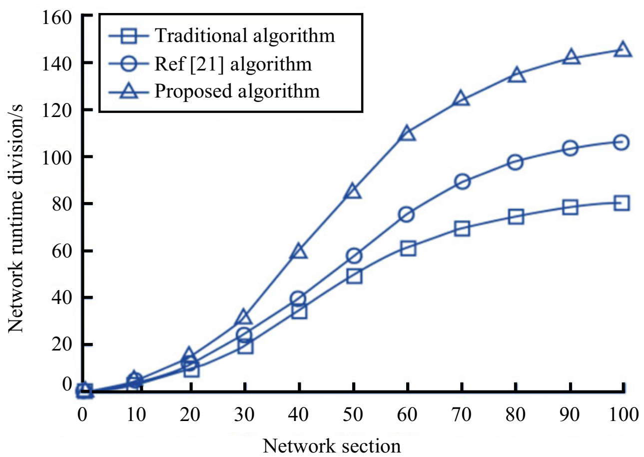

FIGURE 4 Comparison of network lifetime in low-energy environment

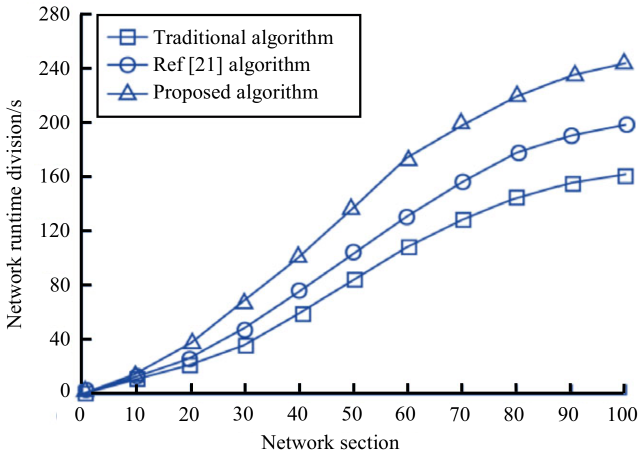

FIGURE 5 Comparison of network lifetime in high-energy environment

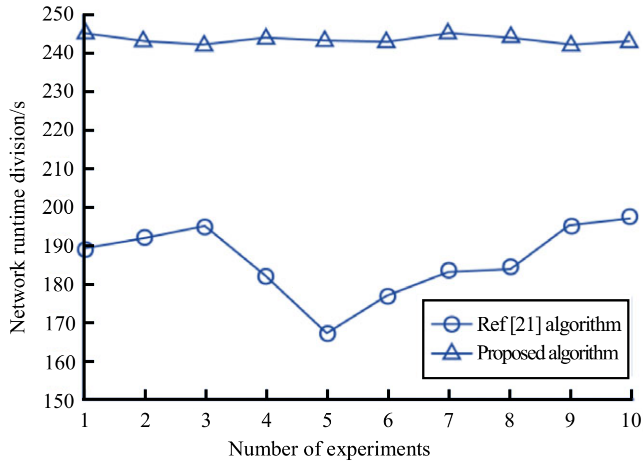

FIGURE 7 Comparison of stability in high-energy environment

its curves are above all of the traditional algorithms. Moreover, as the number of nodes in the network continues to increase, in this study, the rate of increase in the network operation time of the algorithm is longer compared with other algorithms. When the initial energy is 10 J, the running time of the proposed algorithm is 50 seconds higher than that of the literature [21]. When the initial energy is 50 J, the proposed algorithm is 45 seconds higher than the algorithm in [21], which shows that the proposed algorithm can effectively extend the network life.

5.2 | Stability comparison

The stability of the network in practical applications is very important, and is an indicator of the system adaptability. Therefore, after the above network runtime experiments, the algorithm shows good stability. For a network node value of 100 cases, in this study, we conducted 10 experiments and recorded the running time, as shown in Figures 6 and 7.

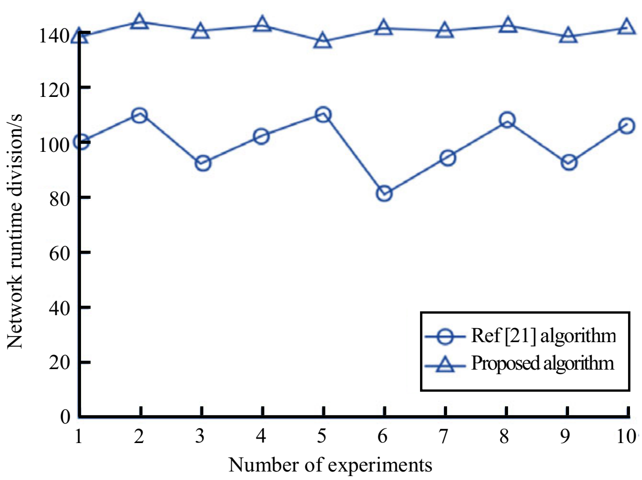

FIGURE 6 Comparison of stability in low-energy environment

It can be seen that the system running time obtained by the proposed algorithm shows high stability under the two kinds of energy environments, with the fluctuating value being between 135 and 145 seconds under low-energy conditions, and between 240 and 247 seconds under high-energy conditions. Compared with [21], the proposed algorithm is considered to have high stability.

5.3 | Comparison of accuracy and data reception

After the above network life and stability of the network contrast experiment, in order to further test the algorithm, the accuracy of the network path selection and data reception rate was chosen to test the data transmission effect and path-selection accuracy of the network. In this study, we use the following definition of the path-selection accuracy:

$$\text{Accuracy} = \frac{\text{Target path node} \cap \text{Path node checked}}{|\text{Target path node}|}. \quad (15)$$

We selected an initial network energy of 50 J. The data transmission efficiency and path-selection accuracy of the network were verified by recording the data of different time periods. The result is shown in Figure 8. The runtime and data reception curve are shown in Figure 9.

As can be seen from Figure 8, as the runtime of the network increases, the accuracy of the path-selection algorithm also increases. However, the accuracy of the proposed algorithm is lower than that of [21] and traditional algorithms during the early stage of network operation (that is before a runtime of 50 seconds). This is because at the beginning of the network, the algorithm needs to collect the information of network nodes in the early stage, and the accuracy increases slowly. However, during the latter periods of the network operation, the accuracy of the proposed algorithm is rapidly improved as sufficient

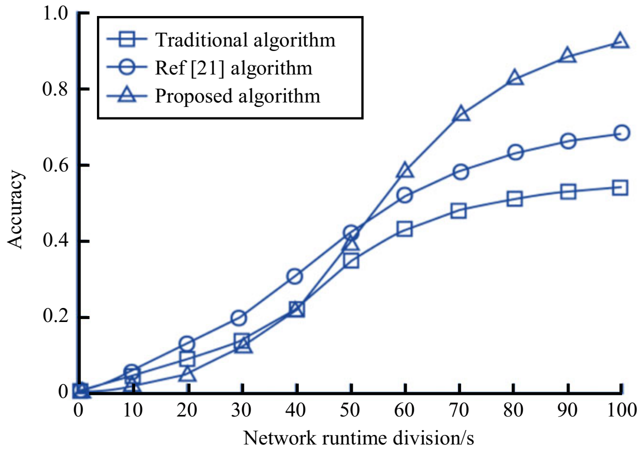

FIGURE 8 Comparison of accuracy of algorithms

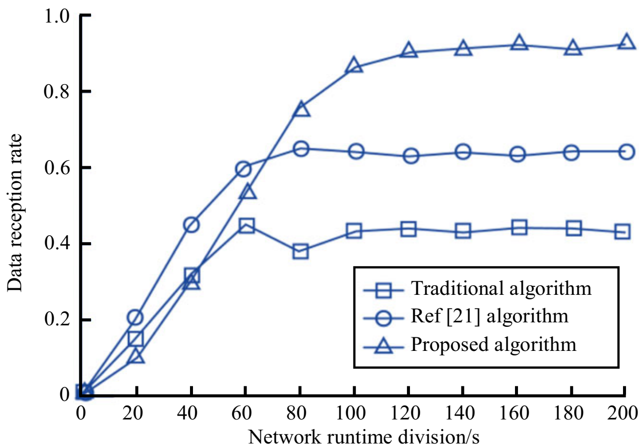

FIGURE 9 Comparison of data reception rate

information becomes available. Therefore, the accuracy of the proposed algorithm is clearly better than that of the other two algorithms. Figure 9 shows the data received by this algorithm and its standard. During the early stage of the network operation, the data reception rate is lower than the corresponding value of the other algorithms, but it starts to increase rapidly after 50 seconds. At the end, the data-receiving rate obtained by the proposed algorithm remained stable at 92%. However, the accuracy of the algorithm in [21] remains stable at 67%, which further verifies the improved data transmission efficiency of the proposed algorithm.

5.4 | Sensitivity analysis

The sensitivity analysis is performed in such a way that when evaluating the performance of a specific outcome, other parameters of Table 1 are kept constant, and only one parameter is changed.

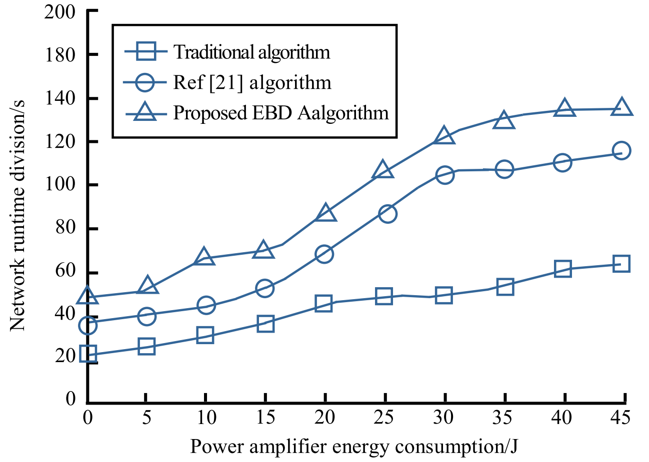

FIGURE 10 Variation of network lifetime with power amplifier energy consumption

5.4.1 | Network lifetime versus power amplifier energy consumption

Figure 10 shows a comparison of the network lifetime versus the power amplifier energy consumption. The outcome is analyzed for different values of power amplifier energy consumption. As can be seen from the figure, the proposed energy balance and dynamic adjustment (EBDA) algorithm shows better network lifetime than its competitors, which makes it more robust and stable for such parametric variations in practical scenarios.

5.4.2 | Network life time versus reference distance between nodes

Figure 11 compares the network lifetime of the algorithms with the reference distance between nodes. It is clear from the figure that when the parameter is varied, the network

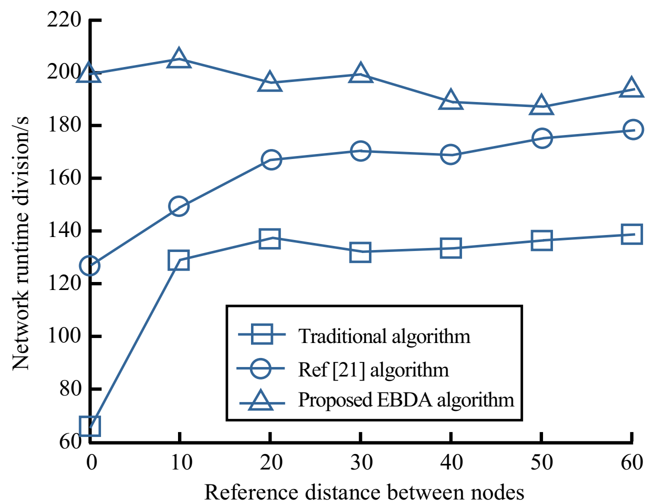

FIGURE 11 Network lifetime against the reference distance between nodes

lifetime is affected. As can be seen, the proposed algorithm shows superior performance compared to the other algorithms. It is also obvious that the network lifetime is optimal for a reference distance between 10 m–30 m.

5.4.3 | Accuracy versus node-energy consumption

Figure 12 compares the accuracy of the algorithms with the node-energy consumption. As can be seen from the figure, the accuracy of the proposed EBDA algorithm is better than that in [21] and the traditional algorithm as the energy consumption of the nodes increases. Moreover, the gap between the proposed algorithm and the traditional algorithm increases, which means that the proposed algorithm can perform better in low- as well as high-energy environments.

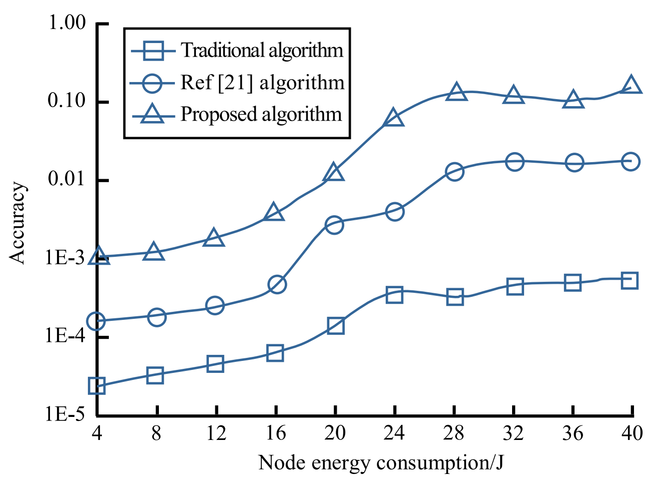

FIGURE 12 Comparison of algorithm accuracy with the node-energy consumption

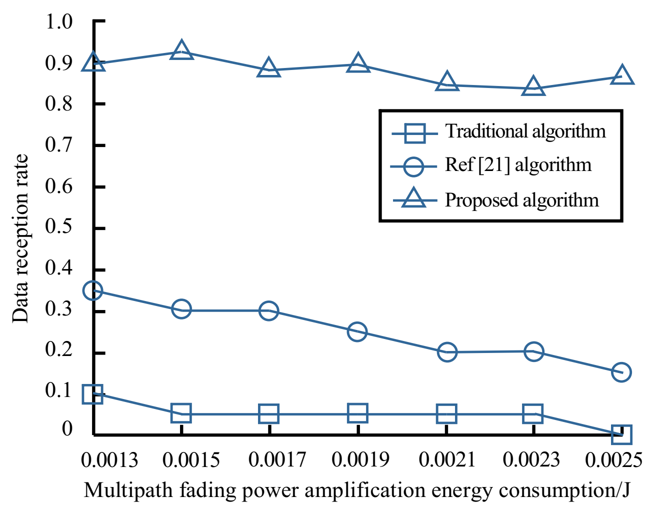

FIGURE 13 Comparison of algorithms data reception rate with the multipath fading power amplification energy consumption

5.4.4 | Accuracy versus node-energy consumption

Figure 13 compares the data reception rate with the multipath fading power amplification energy consumption parameter for the algorithms. As can be seen from the figure, the proposed scheme has a much higher data reception rate than the traditional algorithm and the one reported in [21]. Moreover, the impact of an increasing multipath fading power amplification energy consumption on the proposed EBDA algorithm is negligible, whereas it degrades the data rate of the traditional and reported algorithms [21]. The results clearly reveal that the proposed scheme is more robust than its competitors.

6 | CONCLUSION

This paper presents a load-balancing network node-selection algorithm that is based on the EBDA mechanism. The algorithm optimizes the selection probability and energy according to the characteristics of network nodes. The target path is determined by the association between nodes. The energy consumption factor is introduced to establish the path node-selection mechanism in order to utilize the idle resources of the network to balance the network load. The simulation results show that the proposed algorithm can effectively extend the network life with good stability and accuracy. However, the experiment also found that its accuracy and data reception rate during the preoperation phase of the network system is low, so the algorithm will be optimized as future work. Furthermore, the sensitivity analysis shows that the proposed algorithm has an overall better performance than its competitor's algorithms, which makes it robust to parametric variations in practical usage scenarios.

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