Fault Location Measurement of Sensor Nodes based on Fuzzy Control Algorithm

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Fault location measurement of sensor nodes based on fuzzy control algorithm

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Abstract: Aiming at the problems of the traditional fault location measurement method for sensor nodes, such as more energy consumption and longer measurement time, a fault location measurement method for sensor nodes based on fuzzy control algorithm is designed and proposed. First of all, the fuzzy control algorithm is analyzed; then the clustering based on cluster head diagnosis is carried out for the network, that is, the nodes that meet the cluster head conditions and are set as normal cluster heads are selected as cluster heads. Finally, combined with the fuzzy control algorithm, the fault location of each cluster member node is measured directly by cluster head nodes. The simulation results show that the proposed method has good performance.

Keywords: Fuzzy control algorithm; Sensor; Measurement of node fault location

1. Introduction

With the wide application of WSN in various monitoring systems, the research of WSN is becoming more and more important. At the initial stage of deployment, wireless sensor network nodes are in the state of unmanned monitoring and inspection. The running state of sensor network nodes is unknown, and it is impossible to carry out real-time monitoring or frequent inspection. Once the sensor network fails, it may affect the monitoring production (Qin et al. 2016). Therefore, accurate and timely diagnosis of fault nodes and troubleshooting in wireless sensor network as early as possible, can improve the operation reliability of wireless sensor network, to ensure that the application of the monitoring system in wireless sensor network to complete the scheduled monitoring tasks (Li et al. 2005).

At present, relevant experts have made remarkable research results. For example, Jiang Peng proposed a fault measurement method for sensor node based on improved DFD. DFD algorithm was a node fault diagnosis algorithm that can be applied to wireless sensor network. The fault nodes were measured by data exchange and mutual test between neighboring nodes in the network; Liu Kai et al. proposed a fault location measurement method for sensor nodes in clustering wireless sensor network, which can reduce the measurement error by clustering the nodes. Han Xiaoxiang et al. proposed a fault measurement method for sensor node based on the improved MDLP algorithm and the molecular Brownian motion optimization. Based on the classic MDLP, an improved global data discretization method was designed to effectively carry out all continuous attribute values according to the attribute importance. On the basis of discretization, the difference matrix was used to reduce the feature dimension, and LSSVM which was suitable for small sample data fault diagnosis was used as the fault location measurement model. Although the above methods have achieved very satisfactory research results, they still can not meet the current development needs. In this paper, a fault location measurement method for sensor nodes based on fuzzy control algorithm is designed and proposed. The simulation results fully prove the effectiveness of the proposed method.

2. Methods

2.1 Fuzzy control algorithm

In order to simplify the network, it is specified that the network has the following properties:

(1) The network is a square network (Guo and He 2016; Wu et al. 2018), each node s in the network has a unique ID, assuming that there are N nodes in the network, the node set in the network is expressed as:

$$S = \{s_1, s_2, \cdots, s_n\} \quad (1)$$

(2) After the nodes are randomly deployed, the location of the nodes is fixed;

(3) Each node has the same initial energy, memory, energy consumption for processing information, and the same ability to send and receive information;

(4) The distance between nodes can be estimated by using the received signal strength indication;

(5) After the nodes are deployed, the distance between them and the sink node, the distance between them and the neighbor node, and the number of neighbor nodes are calculated by sending HELLO message (Miao et al. 2019).

When the distance between the nodes is d, the energy consumption of the sensor node transmitting l-bit data is:

$$E_{tx} = \begin{cases} 1 * E_{elec} + \varepsilon_{fs} * d^2, d < d_0 \\ 1 * E_{elec} + \varepsilon_{mp} * d^4, d \geq d_0 \end{cases} \quad (2)$$

Where, E_{elec} is the energy consumed by the transmitting and receiving circuits of the node; ε_{fs} and ε_{mp} are the energy consumption of the circuit amplifier in the short-distance and long-distance data transmission respectively. When the transmission distance $d < d_0$, it is defined as the short-distance; when the transmission distance $d \geq d_0$, it is defined as the long-distance. Then

$$d_0 = \sqrt{\varepsilon_{fs} / \varepsilon_{mp}} \quad (3)$$

The energy consumption of the sensor node receiving l-bit data is as follows:

$$E_{rx} = l * E_{elec} \quad (4)$$

The energy consumption of l-bit data fusion is as follows:

$$E_{DA} = l * E_{pDh} \quad (5)$$

Where E_{pDh} is the energy consumption of l-bit data fusion.

Firstly, the input and output variables of the fuzzy controller are determined. The input variables of the controller are the residual energy of the node (Li and Xia 2016; Ming and Wang 2016; Huynh et al. 2020), the node centrality, the node degree e, the distance from the converging node, and the output variables are the probability that the node is selected as the cluster head and the competition radius.

(1) Residual energy:

The amount of residual energy directly determines the data collection, data fusion and data transmission capacity of the node. Sufficient residual energy is the guarantee of the normal operation of the node;

(2) Node centrality:

The node centrality indicates the importance of the node in the network. The smaller the average shortest distance between the node and the neighbor node is, the higher the node centrality value is, indicating that the node is more important in the region. The value of node centrality can be calculated by formula (6):

$$Node-centrality=\frac{\sqrt{\sum_{j\in N_i} d^2\left(i,j\right)/\left|N_i\right|}}{S_{are}}$$

(6)

Where $\left|N_i\right|$ is the number of neighbor nodes of node i and S_{are} is the area of the calculated sensing area.

(3) Node degree:

Node degree indicates the number of neighbor nodes in the range of node communication. In the process of clustering, the higher the node degree of cluster head is, the lower the transmission cost is.

(4) Distance from sink node: the closer the cluster head is to sink node, the more likely the network "hot spot" problem will occur. Therefore, reducing the cluster size close to the sink node can effectively reduce the impact of "hot spots" on the whole network life (Yang et al. 2016).

(5) The probability that the node is selected as the cluster head: as the first output variable of the fuzzy controller, it is determined by three inputs: the residual energy, the node centrality and the distance from the convergence node. This value indicates the possibility of node becoming cluster head (Wang et al. 2020). The higher the probability of node being selected as cluster head is, the higher the probability of becoming cluster head is. After comparison, the node with the largest value is selected as cluster head.

(6) Competition radius: as the second output variable of the fuzzy controller, it is determined by three inputs: residual energy, node degree and distance from the convergence node. After the first output variable determines the cluster head (Chen 2016; Liu et al. 2016), the value of the output variable represents the competitive radius of the cluster head, that is, determining the size of the cluster.

After the fuzzy control system infers the probability of each node becoming the cluster head and its suitable competition radius, all nodes send information to the neighbor nodes, which includes the node ID and the probability value of the node being selected as the cluster head. After comparison, the node corresponding to the maximum probability value is selected as the cluster head.

In sensor networks, in order to extend the life of nodes with low residual energy, it is often expected to reduce their node degree and reduce their small communication workload; on the contrary, nodes with high residual energy are often expected to increase their node degree and improve communication efficiency. The node degree can be adjusted by controlling the transmission power.

The following gives the numerical relationship of each variable in the system, namely:

$$nd=N\overline{D}+\Delta n\overline{d} \tag{7}$$

$$\Delta nd=nd-ND \tag{8}$$

$$p_u = \overline{p}_u + u \tag{9}$$

$$\Delta e = \overline{E}_{th} - E \tag{10}$$

$$e_1 = K_E \times \Delta e \tag{11}$$

$$e_2 = K_{nd} \times \Delta nd \tag{12}$$

$$e_3 = k_{np} \times \frac{\Delta nd}{\Delta p} \tag{13}$$

$$u = k_U \times U \tag{14}$$

$$\Delta n\overline{d} = k_N \times N \tag{15}$$

The operation process of the whole algorithm is detailed as follows:

Known energy required:

(1) Actual energy of the node (Yang et al. 2016; Shan et al. 2016);

(2) Actual node degree of the node;

(3) Energy threshold;

(4) The expected degree of nodes in the network;

(5) Initial transmitting power of the node;

Algorithm start:

(6) Node’s energy difference = node’s actual energy-energy threshold;

(7) Deviation of the expected node degree;

(8) Target node degree;

(9) Adjustment of node degree;

(10) Transmission power regulation;

(11) Node’s transmit power;

(12) The next hop node determined by the transmission power p is added to the node set of the topology sub network;

(13) The links of all nodes in the connection node set are added to the link set;

(14) End.

2.2 Fault location measurement method of sensor nodes based on fuzzy control algorithm

According to the characteristics of large-scale wireless sensor networks, the fault location measurement method based on clustering mechanism is proposed, and clustering mechanism is considered to be a very effective mechanism to improve the accuracy of fault location measurement in sensor networks. However, these clustering mechanisms do not consider the diagnosis of cluster heads (Xie et al. 2016; Zhang 2016). Therefore, combined with the distributed diagnosis idea of the improved DFD algorithm, a fault location measurement method of sensor nodes based on the fuzzy control algorithm is proposed.

Assuming that sensor nodes are randomly deployed in a rectangular area, all nodes have the same wireless transmission distance d, and the area can be completely covered by the transmission range of sensor network (Zhang and Jiang; Zhao et al. 2019). It is assumed that a large number of nodes are deployed in this area, so there are at least three neighbor nodes in each node's hop range, which can be achieved by properly setting the transmission distance d of the nodes. Each node can communicate with its neighbors in the transmission range, and locate its neighbors through broadcast confirmation protocol.

The model of fault location measurement of sensor node is shown in Figure 1 by using the method of fuzzy control algorithm and neural network. First of all, wireless sensor network collects fault information of sensor nodes, and preprocesses the collected fault information by using relevant signal processing methods, so that the original fault symptom set can be obtained (Yang et al. 2016). Then, the fault diagnosis information reduction algorithm of rough set is used to reduce the fault symptom set and remove the redundant and unimportant symptoms. Finally, the reduced symptom set is used as the input of neural network to measure the fault location of sensor nodes.

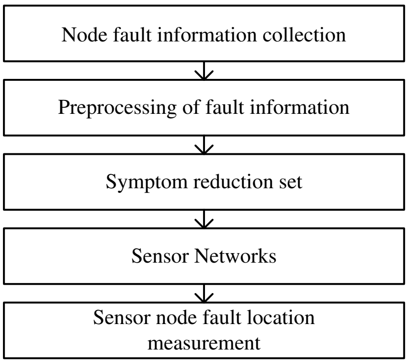


Fig. 1 Fault location measurement model of sensor node

In the fault diagnosis of wireless sensor network, a lot of fault location measurement methods based on fuzzy control algorithm have been proposed, and most of them use BP neural network.

Radial basis function (RBF) neural network is a three-layer forward network. The input layer is composed of signal source nodes; the second layer is the hidden layer, the number of neurons in the hidden layer is determined by the needs of the described problem, and the transfer function of neurons in the hidden layer is radial basis function; the third layer is the output layer, and the transfer function of neurons in the output layer is linear function. Therefore, the transformation from input layer space to hidden layer space is nonlinear, and the transformation from hidden layer space to output layer space is linear.

A radial basis cell model with m inputs is set. It can be seen from the structure of RBN that the transfer function of RBN takes the distance $\|dist\|$ between the input vector p and the weight vector w as the independent variable. The transfer function of the radial basis function neuron has various forms, but the most commonly used form is Gaussian function. Therefore, the transfer function of the radial basis function neural network can be expressed in the following forms:

$$radbas(n) = e^{-n^2} \tag{16}$$

In the neural network, the input layer is used to transmit signals, and the hidden layer is used to adjust the parameters of the transfer function, of which uses the nonlinear optimization strategy, and the learning speed is relatively slow. The output layer adjusts the linear weight and adopts the linear optimization strategy, so the learning speed is relatively fast.

The basic neuron model has m inputs, each of which is connected to the next layer by an appropriate weight w. The network output can be expressed as:

$$a = f(w \cdot p + b) \tag{17}$$

Where, f is the transfer function representing the input / output relationship, a is the output vector, p is the input vector, w is the weight, and b is the threshold.

BP network usually has one or more hidden layers. The neurons in the hidden layer use S-type transfer function, and the neurons in the output layer use linear transfer function. The nonlinear transfer function neuron in the hidden layer can learn the linear and nonlinear relationship between input and output. The linear output layer is to broaden the network output. To limit the network output (such as between 0 and 1), the S-type transfer function can be used.

RBF neural network learning algorithm needs to solve three parameters: the center of the basis function, variance and the weight from the hidden layer to the output layer. According to the different methods of radial basis function center selection, there are many learning methods for RBF network, such as random center selection method, self-organization center selection method, supervised center selection method and orthogonal least square method. The following is the RBF neural network learning method of self-organization selection center, which is composed of self-organization learning and tutor learning stages. The self-organization learning stage is a learning process without tutor. The center and variance of the hidden layer basis function are solved, and the weight between the hidden layer and the output layer is solved in the learning stage.

The commonly used radial basis function in radial basis function neural network is Gaussian function, so the activation function of RBF neural network can be expressed as:

$$R\left(x_p - c_1\right) = \exp\left(\frac{1}{2\sigma^2}\right)\left\|x_p - \right\|_{c_1}^2 \tag{18}$$

Where $\left\|x_p\right\|_{c_1}^2$ is the Euclidean norm, c is the center of the Gaussian function, and σ is the variance of the Gaussian function.

According to the structure of RBF neural network, the output of the network is as follows:

$$y_j = \sum_{i=1}^{h} w_{ij} \exp\left(\frac{1}{2\sigma^2}\right)\left\|x_p - \right\|_{c_1}^2 \tag{19}$$

Where, $x_p = \left(x_1^p, x_2^p, \mathrm{L}\ , x_m^p\right)$ represents the p-th input sample, p represents the total number of samples, c_1 represents the center of the hidden layer node, w_{ij} represents the connection weight from the hidden layer to the output layer, h represents the number of nodes in the hidden layer, y_j represents the actual output of the j-th output node of the network corresponding to the input sample.

Let d be the expected output value of the sample, then the variance of the base function can be expressed as:

$$\sigma = \frac{1}{P}\sum_{j=1}^{m}\left\|d_j - y_j c_i\right\|^2 \tag{20}$$

The specific operation steps of the learning algorithm are as follows:

(1) Based on K-means clustering method, the center c of basis function is obtained

1 Network initialization:

h training samples are randomly selected as cluster center c_i ;

②The input training sample set is grouped according to the nearest neighbor rule:

According to the Euclidean distance between x_p and center c_i, x_p is allocated to the average value of training samples in each cluster set ϑ_p of input samples; if the new cluster center does not change any more, then c_i is obtained, which is the final basis function center of RBF neural network, otherwise ② and the next round of center solution is carried out.

(2) Solve the variance σ_i:

$$\sigma_i = \frac{c_{\max}}{\sqrt{2h}}, i = 1,2,3,\mathrm{L}\ ,h \tag{21}$$

Where $c_{\max}$ is the maximum distance between the selected centers.

(3) The weight between the hidden layer and the output layer is calculated:

$$w = \exp\left(\frac{h}{c_{\max}}\right)\left\|x_p - c_1\right\|^2 \tag{22}$$

The basic idea of BP network learning rule is: the correction of network weight and threshold value should follow the direction of the fastest decline of performance function, negative gradient direction.

$$x_{k+1} = x_k - a_k g_k \tag{23}$$

Where, x_k represents the current weight and closed value matrix, g_k represents the gradient of the current representation function, and a_k is the learning rate.

In the process of measuring the possible states of each node, the probability of the normal node being wrongly measured is:

$$P_{gl\mathrm{g}} = \sum_{i[k,2]}^{k} C_k^i\left(1 - pro\right) \tag{24}$$

On the basis of the above analysis, combined with the fuzzy control algorithm, in each cluster, the cluster head node is used to directly measure the fault location of its member nodes. Then there are

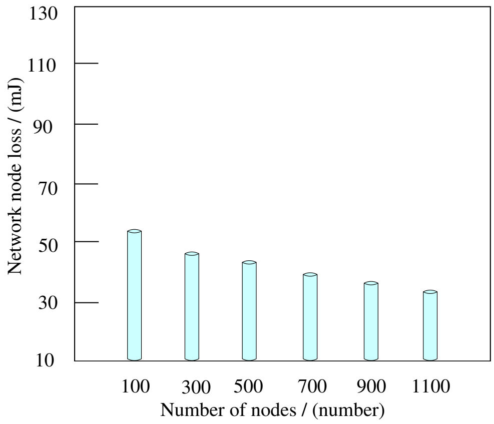
$$P_{cgf} = P_{GG}\left(C_2^{q-\theta^2}\left(1 - pro\right)\right)p * pro \tag{25}$$

3. Simulation experiment

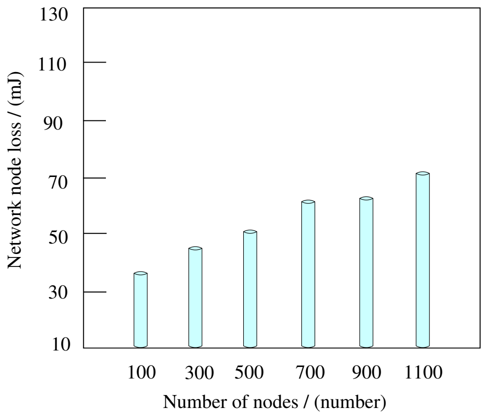
In order to verify the comprehensive effectiveness of the proposed fault location measurement method for sensor node based on fuzzy control algorithm, simulation experiments are needed. The experimental environment is as: Intel (R) Pentium (R) 4, CPU2.30GHz, 2GB memory, Microsoft Windows 7 operating system (64 bit).

(1) Network node loss / (mJ):

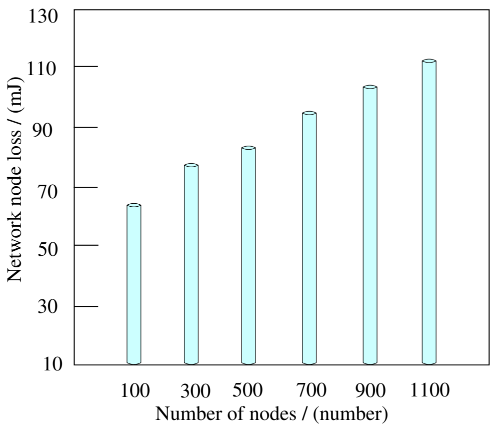
In the following experiments, two traditional measurement methods are selected as comparison methods for simulation experiments. The following experiments mainly compare the network node loss of different methods, and the specific comparison results are shown in the following figure:



(a) Node loss of the proposed method under different network scales



(b) Network node loss of the method in reference [2] under different network scales



(c) Network node loss of the method in reference [3] under different network scales

Fig. 2 Comparison results of network node loss of various measurement methods under different network scales

Table 1 Measurement error changes of the proposed method

Average number of neighbor nodes	Measurement error (%)
100	0.02
200	0.01
300	0.03
400	0.01

500	0.04
600	0.02
700	0.00
800	0.03
900	0.02
1000	0.01
1100	0.00
1200	0.04
1300	0.01
1400	0.03
1500	0.02

Table 2 Measurement error changes of the method in reference (Guo and He 2016)

Average number of neighbor nodes	Measurement error (%)
100	0.04
200	0.06
300	0.08
400	0.11
500	0.13
600	0.17
700	0.20
800	0.24
900	0.28
1000	0.33
1100	0.36
1200	0.39
1300	0.43
1400	0.47
1500	0.51

Table 3 Measurement error changes of the method in reference (Wu et al. 2018)

Average number of neighbor nodes	Measurement error (%)
100	0.04
200	0.06
300	0.08
400	0.11
500	0.13
600	0.17
700	0.20
800	0.24
900	0.28
1000	0.33
1100	0.36
1200	0.39
1300	0.43
1400	0.47

1500	0.51

Analysis of the above experimental data shows that the measurement error of the proposed method is the lowest among the three methods, which shows that the proposed method has high measurement accuracy.

(3) Measurement time / (min):

The measurement time of the three methods is compared as follows, and the specific comparison results are as follows:

Table 4 Measurement time changes of the proposed method

Training times / (time)	Measurement time / (min)
10	12
20	14
30	17
40	18
50	22
60	26
70	30
80	32
90	35
100	38
110	41
120	44
130	47
140	50
150	54
160	58
170	63
180	67
190	71
200	75

Table 5 Measurement time changes of the method in reference (Guo and He 2016)

Training times	Measurement time / (min)
10	45
20	50
30	56
40	62
50	68
60	75
70	80
80	86
90	90
100	95
110	102
120	107
130	112

140	116
150	120
160	125
170	128
180	134
190	140
200	146

Table 6 Measurement time changes of the method in reference (Wu et al. 2018)

Training times	Measurement time / (min)
10	50
20	58
30	67
40	74
50	81
60	90
70	102
80	112
90	120
100	134
110	145
120	153
130	165
140	172
150	183
160	197
170	208
180	212
190	223
200	230

According to the above experimental data, the measurement time of the proposed method is significantly lower than that of the other two methods, which shows that the performance of the proposed method is improved to a certain extent compared with the traditional method.

4. Conclusions

Wireless sensor network is an energy constrained network, a suitable transmission power can greatly reduce energy consumption and internal interference. The fault location measurement of sensor nodes has become one of the most important key technologies. With the development of power control technology in wireless sensor network, fault location measurement technology of sensor nodes has become a new research hotspot (Hung et al. 2020). This paper focuses on the research of fault location measurement of sensor nodes based on fuzzy control algorithm. Although satisfactory research results have been achieved at this stage, there is still a certain follow-up. The following research will be focused on the following aspects:

(1) Definition of the life cycle of the network:

Nowadays, there are many definitions of network life cycle, some of which are not fully or accurately described. A good definition of network life cycle should be related to the current WSN application field.

(2) WSN of 3D network model:

The real application environment of WSN is 3D network model. The node degree of 3D network model is much higher than 2D network model, so it will increase the time complexity of topology construction.

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Figures

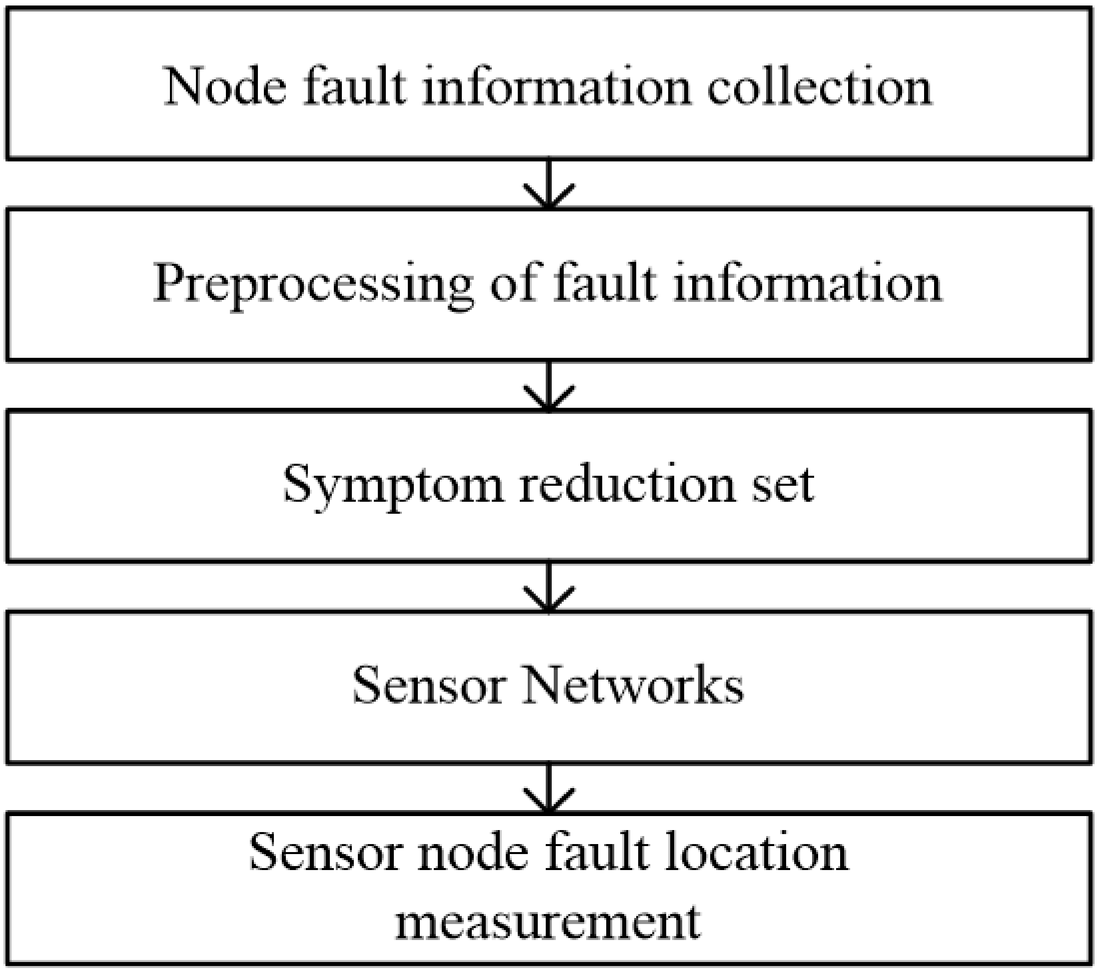

Figure 1

Fault location measurement model of sensor node

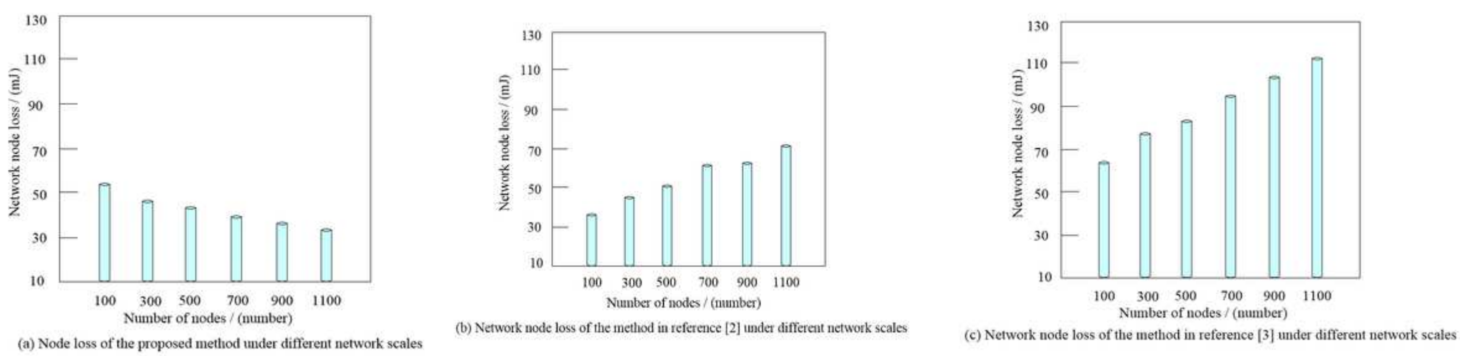

Figure 2

Comparison results of network node loss of various measurement methods under different network scales