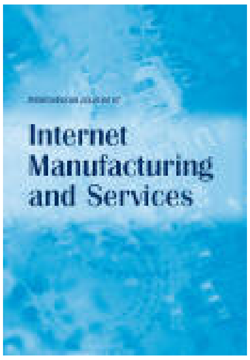

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Fault location method of industrial Ethernet communication line based on Bayesian

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Abstract: Because the traditional fault location method of industrial Ethernet network communication line has the problems of high location false alarm rate, low location accuracy rate and long location time, a Bayesian-based industrial Ethernet network communication line fault location method is proposed. First, the fault signal is measured by discrete Fourier transform algorithm. Then according to the measurement results, the fault features are extracted. Finally, the extracted features are input into Bayesian as training samples, and Bayesian is used to calculate the maximum posterior probability output corresponding to the input data, build a fault localisation model, and obtain the localisation results. The experimental results show that the fault localisation rate of the proposed method is only 0.8%, the localisation accuracy rate is as high as 98.6%, and the localisation time is 10.3 s. The fault localisation effect is good, and the fault localisation time can be effectively shortened.

Keywords: Bayesian; industrial Ethernet network; information entropy; communication line; fault location.

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1 Introduction

As a mature information network technology with advantages of low cost, stability and reliability, Ethernet has the characteristics of random access, carrier sense, collision detection and contention collision (Deng et al., 2022; Jiang et al., 2021; Buhr et al., 2020). However, for occasions with low real-time requirements such as office automation, Ethernet transmission has the disadvantage of uncertain queuing delay, which cannot meet the needs of real-time transmission. Today, with the continuous development of control integration technology, the Ethernet of the management layer continues to expand downward to the device layer, forming a unified transparent data link that does not require data transmission. Therefore, the application of Ethernet technology in the industrial field has been paid more and more attention. With the rapid development of Ethernet technology, the status of industrial Ethernet in industrial control is becoming increasingly prominent. The industrial Ethernet network structure has a high degree of connectivity, and every small line failure in the network communication may cause a large number of alarms. However, fault localisation is mainly about identifying one or more possible causes of alarms by processing the observed alarms (Bugajska et al., 2021; Dashtdar et al., 2021; Hanafy et al., 2021). Therefore, it is of great significance to locate the fault of the industrial Ethernet communication line.

At present, scholars in related fields have carried out research on fault location of network communication lines. Beheshtaein et al. (2019) proposed a communication-based fault location method for high-frequency impedance microgrids. A set of features is first extracted and selected from the measurement signal and fed back to the support vector machine to detect the occurrence of faults. Then, the distributed generator with the lowest fundamental voltage injects the appropriate voltage/current harmonics, which is the generator closest to the fault. Since the impedance value of the fault section is the lowest starting from the point of common coupling of the distributed generation device, the harmonic current value of the corresponding line is the highest. Based on this fact, the first candidate distributed power generation device sends a notification signal to the second candidate distributed power generation system in which a failure occurs between them. Finally, the impedance in the injected frequency is measured from these two distributed generation units and fed into a multi-class support vector machine to locate the faulty line. The method is able to locate faults in islanded and grid-connected microgrids with variable configurations. The simulation results show the effectiveness of the method in grid microgrid. Didehvar and Chabanloo (2019) proposed an accurate estimation method of far-end equivalent impedance for adaptive single-ended fault location. The method is based on measuring the pre-fault voltage and current phasors from the line side without the need for communication links and data synchronisation. Apply the new formula to estimate the Thevenin impedance from the far end of the line. The resulting equivalent impedance can be used to calculate the exact fault location. Using this method, the fault location algorithm can adapt to any network topology changes. To avoid the effect of other load changes on the far-end impedance estimates, a new covariance-based formulation is used. To elucidate the effectiveness of this method, it is applied to a two-sample test network and the results are compared with three other methods. The simulation results show that the method proposed in this paper has sufficient adaptability to network topology changes and is robust to network side load changes. Pan et al. (2019) proposed a fault location method for relay protection communication system based on multi-source data of power grid operation and maintenance. Based on the warning information of the relay protection management system and the communication network management system, combined with the operation management system information, firstly identify the fault area to narrow the fault location judgement range, and then use the historical operation and maintenance data in the fault area. After the prior probability is obtained, the fault probability is calculated by the improved Bayesian algorithm, the fault cause is inferred, and the fault location is judged according to the information of the communication resource management system. The results of example analysis demonstrate the effectiveness and accuracy of the method. This method is also suitable for multi-region concurrent fault location. However, the above methods still have the problems of poor fault location, low accuracy and long time.

Aiming at the above problems, this paper studies a Bayesian-based fault location method for industrial Ethernet communication lines. The specific technical route studied in this paper is as follows:

Step 1 Analyse the industrial Ethernet communication line fault signal after discrete Fourier transform as a signal source, and obtain the energy distribution of each frequency point on the industrial Ethernet communication line fault signal spectrum according to the probability distribution calculation. And set a fixed threshold to measure the fault signal of the industrial Ethernet communication line.

Step 2 According to the measurement result of the fault signal of the industrial Ethernet communication line, calculate the information entropy value and the approximate entropy value at the fault and normal position of the industrial Ethernet communication line respectively, and extract the fault characteristics of the industrial Ethernet communication line.

Step 3 Input the extracted industrial Ethernet communication line fault features as training samples into Bayesian. The maximum posterior probability output corresponding to the input data is calculated, the fault location model of the industrial Ethernet network communication line is constructed, and the fault location of the industrial Ethernet network communication line is realised.

2 Design of fault location method for industrial Ethernet communication line

2.1 Industrial Ethernet communication line fault signal measurement

In order to effectively realise the fault location of the industrial Ethernet network communication line based on Bayes, and ensure the safety and stability of the communication operation of the industrial Ethernet network. Firstly, the fault signal of the industrial Ethernet network communication line after the discrete Fourier transform is analysed as the signal source, and the energy distribution of each frequency point on the fault signal spectrum of the industrial Ethernet network communication line is obtained according to the probability distribution calculation (Özcan and Rosenberg, 2020; Yang et al., 2022; Xie and Wu, 2020). And set a fixed threshold to eliminate the interference phenomenon caused by noise, and complete the measurement of the fault signal of the industrial Ethernet communication line.

The energy threshold is set as α, and the signal sampling sequence of the fault point Q of the industrial Ethernet communication line is w_e and $e = 0, 1, \ldots, Q-1$. The information entropy acquisition process of the industrial Ethernet communication line fault signal is as follows.

Through the discrete Fourier transform algorithm (Lyons and Howard, 2021; Fedorenko, 2020; Sharma and Garg, 2021), the fault signal of the industrial Ethernet network communication line is calculated, and the obtained signal is analysed as the signal source. The results are as follows:

$$E(r) = \sum_{e=0}^{Q-1} w_e \times y^{-u \times \frac{2\beta}{Q} \times e \times r}, r = 0, 1, \ldots, Q-1 \tag{1}$$

In formula (1), $E(r)$ is the source analysis result of the industrial Ethernet communication line fault signal, Q is the fault point of the industrial Ethernet communication line, r is the source analysis quantity, and y is the discrete Fourier transform coefficient. e is the number of sampling sequences of industrial Ethernet communication line fault signals, β is the transmission radius of industrial Ethernet communication line fault signals, and u is the index.

Based on the energy calculation method, the construction probability distribution of the industrial Ethernet communication line fault signal is calculated, and the probability distribution vector of the industrial Ethernet communication line fault signal is obtained. The result is as follows:

$$R = \{p_r\} = \frac{E_r}{\sum_{r=0}^{Q-1} E_r} \times E(r) \tag{2}$$

In formula (2), $\{p_r\}$ is each element in the vector, and E_r is the probability distribution model of the industrial Ethernet communication line fault signal.

According to the calculation formula of information entropy (Xu and Luo, 2019; Qin et al., 2022), the sampling sequence of the industrial Ethernet communication line fault signal is calculated, and the information entropy statistical value of the industrial Ethernet communication line fault signal in the frequency domain is obtained, and the obtained results are as follows:

$$Y = -R \sum_{r=0}^{Q-1} o_r \log o_r \tag{3}$$

In formula (3), o_r is the fault signal element of the industrial Ethernet communication line, and log is the activation function. According to the calculation results, the overall distribution of the time factor to the fault spectrum characteristics can be avoided, and the information entropy index value is defined according to the obtained distribution results. The result looks like this:

$$a(s_i) = \sin 2\pi Y s_i d_1 \times d_2 \times d_3 \tag{4}$$

In formula (4), s_i is the fault signal frequency of the industrial Ethernet communication line, and d_1, d_2, d_3 is the different entropy values of the three ideal signals.

In order to reduce the impact of fault diversity and fault complexity on fault signal metrics. Set the information entropy of the fault signal of the industrial Ethernet communication line to A_1, and the entropy of the normal signal of the industrial Ethernet communication line to A_0. The obtained information entropy of the fault signal of the industrial Ethernet communication line is as follows:

$$A = \frac{A_1}{A_0} \tag{5}$$

Set the approximate entropy of the fault signal of the industrial Ethernet communication line as S_1, and the approximate entropy of the signal at the normal position of the industrial Ethernet communication line as S_0, and the obtained approximate entropy index is as follows:

$$S = \frac{S_1}{S_0} \tag{6}$$

Compared with the above-mentioned signal information entropy in the frequency domain, the approximate entropy index of the signal is based on the time domain perspective to measure the fault signal of the industrial Ethernet communication line.

2.2 Feature extraction of industrial Ethernet communication line faults

On the basis of measuring the fault signal of the industrial Ethernet network communication line, the fault characteristics of the industrial Ethernet network communication line are extracted.

Based on the obtained industrial Ethernet communication line fault entropy index, the overall signal in the frequency domain is measured, and the measured index value changes with the change of the initial angle of the voltage at the industrial Ethernet communication line fault. When the fault initial angle $\gamma_0 \leq 90°$ of the industrial Ethernet communication line. The information entropy index of the fault signal of the industrial Ethernet communication line will increase according to the increase of the high frequency component of the signal, and the approximate entropy index will decrease with the decrease of the low frequency component. First, calculate the information entropy value and approximate entropy value at the fault of the industrial Ethernet communication line, and then calculate the information entropy value and approximate entropy value at the normal place of the industrial Ethernet communication line. The calculation results are as follows:

$$\begin{cases} A_a = \dfrac{A_{1a}}{A_{0a}} \\ A_b = \dfrac{A_{1b}}{A_{0b}} \\ A_c = \dfrac{A_{1c}}{A_{0c}} \\ S_a = \dfrac{S_{1a}}{S_{0a}} \\ S_b = \dfrac{S_{1b}}{S_{0b}} \\ S_c = \dfrac{S_{1c}}{S_{0c}} \end{cases} \tag{7}$$

In formula (7), A_{1a}, A_{1b}, A_{1c} is the information entropy value of each current when the industrial Ethernet communication line fails, and S_{1a}, S_{1b}, S_{1c} is the corresponding approximate entropy value. A_{0a}, A_{0b}, A_{0c} is the current entropy value of the normal position of the industrial Ethernet communication line, and S_{0a}, S_{0b}, S_{0c} is the corresponding approximate entropy value.

Through the calculation of different information entropy indicators, the extraction of fault characteristics of industrial Ethernet communication lines is completed. The extraction results are as follows:

$$D_i = \frac{1}{2}\left[(A_i - 1)\delta + 1\right] + \frac{1}{2}S_i \tag{8}$$

In formula (8), $[(A_i - 1)\delta + 1]$ is the unification process of the transformation between the index value A_i and the approximate index value S_i, and δ is the standard index.

2.3 Construction of a Bayesian-based fault location model

Bayesian is a theorem about the conditional probability of random events *A* and *B* based on the assumption of conditional independence (Liakoni et al., 2021; Peng et al., 2020; Bhattacharya and Maiti, 2021). For the training sample set, the joint probability distribution function of the input and output in the training set is firstly calculated. Based on this, the maximum posterior probability output corresponding to the input data is calculated by Bayesian.

After extracting the fault characteristics of the industrial Ethernet communication line, input it as a training sample into Bayesian, and then the fault location model of the industrial Ethernet communication line can be constructed to realise the fault location of the industrial Ethernet communication line.

In the process of fault location of industrial Ethernet communication lines, the application of posterior probability is involved, and the parameter calculation process is as follows:

1 Line protection refusal probability: Refers to the state probability that no action occurs at the protection location when the industrial Ethernet communication line element fails within the protection range. The calculation formula is:

$$P_j = \frac{\varepsilon}{\epsilon + \varepsilon} \tag{9}$$

In formula (9), ε represents the number of times of protection refusal to act within the unit time range, and ϵ represents the number of correct actions at the protection location within the unit time range.

2 Line element failure probability: Under normal circumstances, the state change probability of an industrial Ethernet communication line element is only related to its current state. Then, the calculation formula of the failure probability of industrial Ethernet communication line components in the unit time range is:

$$P_k(\Delta t) = 1 - e^{-\theta \times \Delta t} \approx \theta \times \Delta t \tag{10}$$

In formula (10), Δt represents the unit time range, and θ represents the number of failures of the industrial Ethernet communication line components within the unit time range.

3 Probability of misoperation of line protection: It refers to the probability that the communication line components of the industrial Ethernet network have no faults within the unit time range, but the probability of action occurring at the protection point. The calculation formula is:

$$P(\Delta t) = \vartheta \times \Delta t \tag{11}$$

In formula (11), ϑ represents the number of malfunctions of the protection within the unit range.

Through Bayesian, we can observe the connection between industrial Ethernet communication line components, protection at all levels and circuit breakers, combined with the calculation of mathematical probability. Then, the fault location model of the industrial Ethernet network communication line can be constructed to realise the fault location of the industrial Ethernet network communication line.

In the process of fault location processing of industrial Ethernet communication lines, it is necessary to perform high-resolution conversion on it, and process the conversion result accordingly. Under normal circumstances, the fault location calculation process of the industrial Ethernet communication line is as follows.

Extracting the maximum value μ_{fa} of the conversion coefficient before the fault of a certain industrial Ethernet communication line element f, and extracting the maximum value μ_{fb} of the conversion coefficient after the fault, then the calculation formula of the magnitude of change in the electrical quantity of the industrial Ethernet communication line is:

$$\rho_i = \frac{\max\left(\mu_{fa}, \mu_{fb}\right)}{\min\left(\mu_{fa}, \mu_{fb}\right)} \tag{12}$$

Therefore, the calculation formula of the electrical quantity amplitude fault of the industrial Ethernet communication line is obtained as:

$$\sigma_i = \frac{\rho_i^2}{\rho_1^2 + \rho_2^2 + \cdots + \rho_n^2} \tag{13}$$

Arrange the extracted fault characteristics of industrial Ethernet communication lines into a matrix form, and obtain the diagonal matrix as τ through singular decomposition, then the calculation formula for the singular point faults of industrial Ethernet communication lines is:

$$\varphi_i = \sum\nolimits_{i=1}^{n} \omega_i \times \tau \tag{14}$$

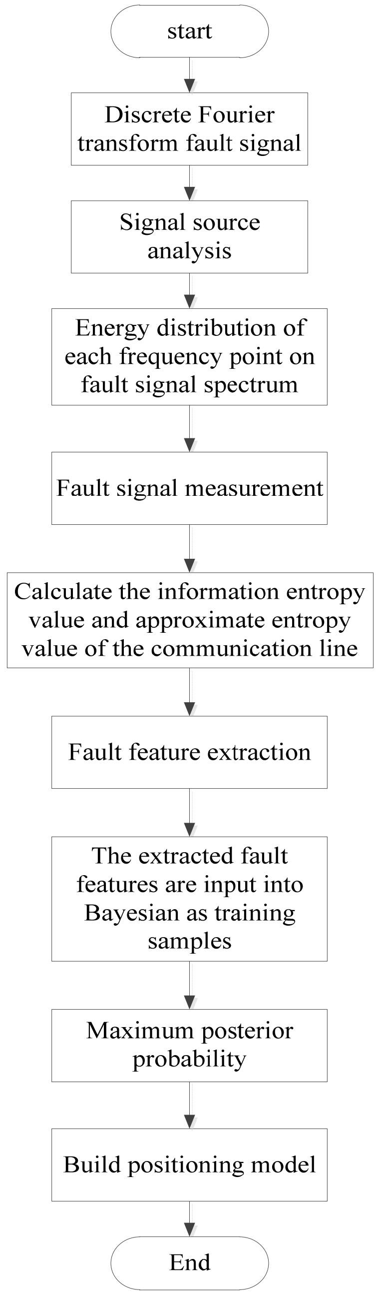
In formula (14), ω_i represents the first element in the diagonal matrix.

The electrical quantity amplitude fault and singular point fault of the industrial Ethernet communication line obtained above are fused to obtain the fusion characteristic information $\beth_i$, which is used to train Bayesian and judge the connection between the various components of the industrial Ethernet communication line. The maximum posterior probability is solved by joint conditional probability, and the fault location model of industrial Ethernet communication line is constructed. The calculation formula is as follows:

$$\aleph = \sum\nolimits_{i=1}^{n} \beth_i \times \frac{\sigma_i + \varphi_i}{D_i} \times \left(P_j + P_k(\Delta t) + P(\Delta t)\right) \tag{15}$$

Through the above process, a Bayesian-based industrial Ethernet communication line fault location is realised, and the specific process is shown in Figure 1.

Figure 1 Specific process of fault location of industrial Ethernet communication line based on Bayesian



3 Experimental protocols

3.1 Experimental data

In order to verify the effectiveness of the Bayesian-based industrial Ethernet communication line fault location method, the experiment uses Java language to build an industrial Ethernet experimental environment, and uses Matlab tools to process the experimental data. The hardware environment of this experiment is IBM server, the background database is MongoDB 2.2.6, and the operating system environment is CentOS 6.4 64-bit. Select 1,000 MB of industrial Ethernet communication line fault data, of which 500 MB is used as the fault training set, and the other 500 MB is used as the fault test set. To locate the fault of the communication line of the industrial Ethernet network, the method of Beheshtaein et al. (2019), the method of Didehvar and Chabanloo (2019) and the proposed method are used to compare and verify the effectiveness of the proposed method.

3.2 Selection and calculation of performance indicators

According to the experimental dataset above, combined with the selection and calculation of performance indicators, the fault location effect, fault location accuracy, and fault location time are used as performance indicators for analysis. Among them, the fault location missed rate is used as the evaluation index of the fault location effect. The lower the fault location missed rate is, the better the fault location effect of the method is. It is calculated as follows:

$$L_B = \frac{L_Z}{G_Z} \tag{16}$$

In formula (16), L_Z represents the fault location data of the industrial Ethernet communication line that is not reported, and G_Z represents the fault data of the industrial Ethernet network communication line to be located. The fault location accuracy rate is used as the evaluation index of the fault location accuracy. The higher the fault location accuracy rate, the higher the fault location accuracy of the industrial Ethernet communication line of the method. It is calculated as follows:

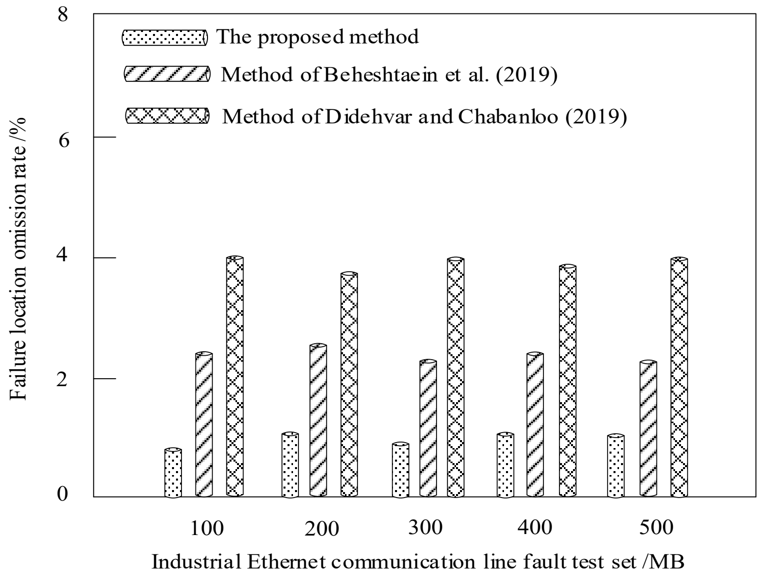
$$A_C = \frac{Z_Q}{G_Z} \tag{17}$$

In formula (17), Z_Q represents the correctly located fault data of the industrial Ethernet communication line.

3.3 Testing and analysis of performance indicators

In order to verify the fault location effect of the proposed method in the communication line of the industrial Ethernet network, formula (16) is used to calculate the fault location missed rate. The method of Beheshtaein et al. (2019), the method of Didehvar and Chabanloo (2019) and the proposed method are used to compare, and the fault location and false alarm rate of industrial Ethernet communication lines of different methods are obtained as shown in Figure 2.

Figure 2 Fault location miss rate of industrial Ethernet communication line with different methods

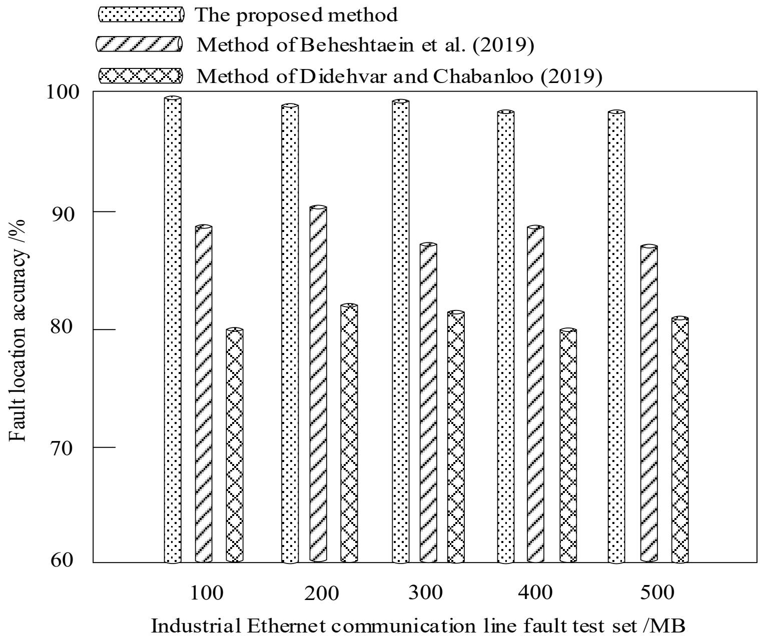


According to Figure 2, when the industrial Ethernet communication line fault test set is 500 MB, the average industrial Ethernet communication line fault location false negative rate of the method of Beheshtaein et al. (2019) is 2.2%. The average industrial Ethernet communication line fault location false negative rate of the method of Didehvar and Chabanloo (2019) is 3.8%. However, the average industrial Ethernet communication line fault location missed-report rate of the proposed method is only 0.8%. It can be seen from this that the proposed method has a low false alarm rate for fault location of industrial Ethernet communication lines, and has a good effect of fault location of industrial Ethernet communication lines.

To further verify the accuracy of fault location of industrial Ethernet communication lines of the proposed method, the correct rate of fault location is calculated by formula (17). The method of Beheshtaein et al. (2019), the method of Didehvar and Chabanloo (2019) and the proposed method are used to compare, and the correct rate of fault location of industrial Ethernet communication lines of different methods is obtained as shown in Figure 3.

According to Figure 3, when the industrial Ethernet communication line fault test set is 500 MB, the average industrial Ethernet communication line fault location accuracy rate of the method of Beheshtaein et al. (2019) is 88.6%. The average fault location accuracy rate of the method of Didehvar and Chabanloo (2019) is 81.5% for industrial Ethernet communication lines. The average fault location accuracy rate of the proposed method is as high as 98.6% for industrial Ethernet communication lines. It can be seen from this that the proposed method has a higher accuracy of fault location of the industrial Ethernet communication line, and can effectively improve the accuracy of the fault location of the industrial Ethernet communication line.

Figure 3 Correct rate of fault location of industrial Ethernet communication line with different methods



On this basis, the fault location time of the industrial Ethernet communication line of the proposed method is further verified. Comparing the method of Beheshtaein et al. (2019) and the method of Didehvar and Chabanloo (2019) with the proposed method, the fault location time of industrial Ethernet communication lines of different methods is obtained as shown in Table 1.

Table 1 Fault location time of industrial Ethernet communication line by different methods

Industrial Ethernet communication line failure test set / MB	*The proposed method / s*	*The method of Beheshtaein et al. (2019) / s*	*The method of Didehvar and Chabanloo (2019) / s*
100	2.1	5.5	8.3
200	4.3	7.9	11.2
300	5.9	10.6	13.7
400	8.1	12.7	16.9
500	10.3	15.3	19.6

According to Table 1, with the increase of industrial Ethernet communication line fault test sets, the fault location time of industrial Ethernet communication lines of different methods increases. When the industrial Ethernet communication line fault test set is 500 MB, the fault location time of the industrial Ethernet communication line in the method of Beheshtaein et al. (2019) is 15.3 s. The fault location time of the industrial Ethernet communication line in the method of Didehvar and Chabanloo (2019) is 19.6 s. However, the fault location time of the proposed method for industrial Ethernet communication lines is only 10.3 s. It can be seen that the fault location time of the industrial Ethernet communication line of the proposed method is short.

4 Conclusions

The Bayesian-based industrial Ethernet communication line fault location method proposed in this paper can give full play to the advantages of Bayesian and effectively locate the industrial Ethernet communication line fault. Its industrial Ethernet communication line fault location missed report rate is only 0.8%, the fault location accuracy rate is as high as 98.6%, and the fault location time is only 10.3 s. It has better fault location effect and high fault location accuracy, and can effectively shorten the fault location time. However, this method only calculates the fault correlation coefficient for the communication line components of the industrial Ethernet network, and does not consider the topology analysis. Therefore, in the next step, the part of topology analysis needs to be further studied.

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