Fault location of secondary equipment in smart substation based on switches and deep neural networks

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Abstract. With the continuous development of smart substations, the functions of switches have been continuously improved. To improve the efficiency of the operation and maintenance of secondary equipment, this article proposes a fault location method for secondary equipment in smart substations based on switches and deep neural networks. First, the key alarm signal capture function and traffic statistics function are configured on the switch. Secondly, based on alarm information, traffic statistics, and message subscription relationships, the representation of the fault feature information method is proposed. Using the training rules of deep learning, the fault location model of secondary equipment based on deep neural network is established and the fault location steps are given. Taking the line spacing of smart substations as an example, simulations verify the effectiveness of the fault location method, and good location results can still be obtained in an environment with insufficient feature information reliability.

1. Introduction
The smart substation has a large number of networked secondary equipment [1-2], and its reliability directly determines whether the smart substation can operate stably. At present, the fault location of secondary equipment is mainly determined by technicians based on the alarm signal [3]. However, due to a large number of alarm signals and the lack of effective analysis methods, much key information is missing, it is impossible to accurately locate the secondary equipment fault.

At first, some scholars proposed to locate the fault of secondary equipment based on the SCD file of the smart substation [4-7]. This method is simple and easy to implement, however, it should be noted that due to the different configuration tools of the smart substation, the standardization of the SCD file is poor, and there are multiple solutions for the topology between the secondary equipment, therefore, the method of using only the SCD file to locate the fault of the secondary equipment still has disadvantages such as poor versatility. Ye combines the function of the network message analysis equipment and configures the correspondence between the information flow and the IED in the secondary system to extract part of the message to analyze the operating state of the secondary equipment [8]. However, there are few fault features selected by this method, so only the approximate fault range can be judged. Wang proposed an evaluation model including relay protection loop nodes
based on the trapezoidal cloud model [9]. Xu proposed to combine secondary equipment self-test 
information and historical data to estimate the operating state of related secondary equipment [10]. 
The above two pieces of literature consider the influence of many factors, but there is a problem that 
the weight value is not objective in the evaluation process. Besides, because of a large amount of data 
and the presence of noise interference, its ability to deal with big data is weak.

In summary, the currently proposed methods are unable to quickly and accurately locate the faults 
of the secondary equipment. The reasons are as follows:

- There are many types of secondary equipment and the types of faults are complex, but the 
  fault criteria are few and the correlation is weak.
- The amount of data during secondary equipment fault is large, and conventional methods 
  cannot achieve efficient and rapid analysis.
- The generated alarm information may have problems such as distortion and loss during the 
  collection process, which causes the fault location results to fluctuate according to the 
  different confidence levels of the alarm information.

In response to the above problems, this article proposes a method for fault location of secondary 
equipment in smart substations based on switches and deep neural networks, which opens a new path 
for breaking the current fault location bottleneck.

Fault fe

ture information is obtained by configuring 
the key alarm signal capture function and the traffic statistics function on the switch. Based on alarm 
information, traffic statistics, and message subscription relationships, the characterization method of 
fault feature information is proposed. Using the deep learning training method, a DNN-based 
secondary equipment fault location model is established and the fault location steps are given. Taking 
the line interval as an example, the simulation verifies the eff

tectiveness of the fault location method, 
and it can still achieve good location results in the environment with insufficient reliability of feature 
information.

2. Analysis of Fault Feature Information

2.1. Fault alarm and traffic statistics

At present, the secondary equipment in smart substations often uses networking to transmit messages. 
As a transfer medium, the functions of switches are constantly improving and developing. To obtain as 
much information about the fault features of the secondary equipment as possible, the key alarm signal 
capture function and the traffic statistics function can be configured on the switch. When the 
secondary equipment fails, the abnormal equipment alarm signal will be issued first, and these alarm 
signals will be captured by the neighboring switch. Secondly, the traffic of messages sent by the faulty 
secondary equipment will drop sharply, and at this time, the neighboring switch will quickly send out 
an alarm signal for the abnormal message traffic. Besides, according to the message subscription 
relationship in the SCD file, because the relevant sink cannot normally receive the message from the 
faulty secondary equipment, it will also send out abnormal message reception alarm signals, which 
will be captured by the switch near the sink [11-14].

In this article, combined with the actual operating conditions of smart substations and the way to 
obtain fault samples, the selected fault location objects include the merge unit (MU), intelligent 
terminal, and protection equipment. Besides, different alarms will be generated when different 
modules of the secondary equipment fail. The alarm signal generated when some modules fail is 
simple, and the operation and maintenance personnel can quickly identify the fault location, for 
example, if the secondary equipment loses power, a power fault alarm will occur, therefore, to 
improve the convergence speed of the model, this type of fault is not involved in the subsequent 
research. The remaining 8 types of faults are shown in Table 1.

| Number | Fault location               |
|--------|------------------------------|
| 1      | The DSP module of the MU     |
Number | Fault location
--- | ---
1 | The DSP module of the MU
2 | The I/O module of the MU
3 | The CPU plug-in of protection equipment
4 | The I/O plug-in of protection equipment
5 | The SV plug-in of protection equipment
6 | The GOOSE plug-in of protection equipment
7 | The CPU board of intelligent terminal
8 | The I/O board of intelligent terminal

The alarm signal generated when the above-mentioned fault occurs can be roughly divided into abnormal equipment alarm, abnormal message traffic alarm, and abnormal message reception alarm. Since the alarm signals of the secondary equipment produced by different manufacturers are slightly different when the secondary equipment fails, to enrich the application scenarios of the model, the alarm signals with strong versatility are selected as the fault feature, as shown in Table 2. Alarms for abnormal message traffic and abnormal message reception depend on the status of the information flow in the communication network. These alarm signals are the data foundation that supports the accurate location of secondary equipment faults.

### Table 2. Fault Alarms

| Type | Name |
|------|------|
| Abnormal equipment alarms | Abnormal equipment alarm of MU, Synchronization exception of MU, Total SV alarm of MU, Total GOOSE alarm of MU, Abnormal equipment alarm of protection equipment, Protection blocking, Protection memory error, Protection (Start) verification error, Protection (Start) sampling error, Total SV alarm of protection equipment, Total GOOSE alarm of protection equipment, Abnormal sampling quality of protection, Reclosing blocking, Abnormal equipment alarm of intelligent terminal, Memory error in the intelligent terminal |

#### 2.2. Characterization of fault feature information

Using the above alarm signals, the fault feature set $X_i$ can be characterized as shown in (1).

$$X_i = [X_{\text{AEA}}, X_{\text{AMTA}}, X_{\text{AMRA}}], i = 1, 2, ..., N$$

(1)

In (1): $X_i$ represents the fault feature set of the $i$-th fault event, which includes abnormal equipment alarms $X_{\text{AEA}}$, abnormal message traffic alarm $X_{\text{AMTA}}$, and abnormal message reception alarm $X_{\text{AMRA}}$. $N$ is the total number of fault events.

$X_{\text{AEA}}$ integrates the self-check state of the MU, protection equipment, and the intelligent terminal, as shown in (2).

$$X_{\text{AEA}} = X_{\text{MU}_1}, X_{\text{MU}_2}, ..., X_{\text{MU}_{k}}, X_{\text{P}_1}, X_{\text{P}_2}, ..., X_{\text{P}_m}, X_{\text{IT}_1}, X_{\text{IT}_2}, ..., X_{\text{IT}_{n}}$$

$$X_{\text{MU}_{a}} = [S_{\text{can}}, S_{\text{ex}}, S_{\text{an}}, ...]$$

$$X_{\text{P}_{b}} = [S_{\text{can}}, L_{\text{out}}, M_{\text{er}}, C_{\text{er}}, ...]$$

$$X_{\text{IT}_{c}} = [S_{\text{can}}, M_{\text{er}}, C_{\text{er}}, ...]$$

(2)

In (2): $k$, $m$, and $n$ are the total number of merging units, protection equipment, and intelligent terminals in the secondary system, respectively. $X_{\text{MU}_{a}}$, $X_{\text{P}_{b}}$, and $X_{\text{IT}_{c}}$ are the abnormal equipment alarms of the $a$-th merging unit, the $b$-th protection equipment, and the $c$-th intelligent terminal, including the self-check abnormality alarm $S_{\text{can}}$, the synchronization abnormality alarm $S_{\text{ex}}$, the sampling abnormality alarm $S_{\text{an}}$, and the protection lockout $L_{\text{out}}$. Memory error $M_{\text{er}}$, verification error $C_{\text{er}}$, and others.
If the background monitoring detects the feature information when the fault occurs, the corresponding location element is 1, otherwise, it is 0.

The abnormal message traffic alarm $X_{AMTA}$ integrates the traffic status of the messages received by all switch ports in the secondary system, as shown in (3).

$$
X_{AMTA} = [S_1, S_2, \ldots, S_n]
$$

$$
S_c = [P_1, P_2, \ldots, P_M]
$$

$$
P_j = [A_{AMT_1}, A_{AMT_2}, \ldots, A_{AMT_m}]
$$

In (3): $N$ is the total number of switches. $S_c$ is the port information of the $c$-th switch in the secondary system, where $P_j$ is the state of the message traffic through the switch port $j$, which contains $m$ pieces of traffic information. During the monitoring process, if it is found that the traffic of the $k$-th message through this port is too low, $A_{AMT_k}$ is 1, otherwise, it is 0.

The abnormal message reception alarm $X_{AMRA}$ integrates the SV/GOOSE message reception status including the merging unit, protection equipment, intelligent terminal, and measurement and control equipment, as shown in (4).

$$
X_{AMRA} = [R_1, R_2, \ldots, R_j, \ldots, R_{num}]
$$

$$
R_j = [D_{j1}, D_{j2}, \ldots, D_{jm}]
$$

2.2.1. In (4): $num$ is the total number of messages in the communication network. $R_j$ is the receiving state of the $j$-th message, including the receiving state $D$ of $m$ secondary equipment that subscribes to the message. If the secondary equipment $x$ does not receive the message $j$, then $D_{jx}$ is 1, otherwise, it is 0.

3. DNN-Based Secondary Equipment Fault Location Model

Due to the complexity of the alarm information when the secondary equipment fails, it is difficult to accurately locate the fault module, so this article selects DNN to build the secondary equipment fault location model [15-16]. The basic structure of DNN is shown in Figure 1.

The output $y^q_n$ of the neuron $q$ of the $n$-th layer in the DNN is shown in (5), which depends on the output $y^{n-1}_i$ of all neurons in the upper layer, the connection weight $\omega^q_{ii}$, the linear bias $b^q_i$, and the activation function $\sigma$ used.

$$
y^q_n = \sigma(z) = \sigma \left( \sum_{i=1}^{n} \omega^q_{ii} y^{n-1}_i + b^q_i \right)
$$

Generally, when calculating the loss function, all training samples need to be taken as the object, and the sum of the loss functions is calculated as the network learning index, as shown in (6).

$$
E = \sum_n E_n
$$
In (6): $E_n$ is the loss function corresponding to the $n$-th data.

However, if the loss function is calculated in this way, as the future data samples increase, the training time of the model will greatly increase, so this article uses the mini-batch learning method. Besides, when Sigmoid is used as the activation function of forwarding propagation, if the loss function uses cross-entropy, the training speed of the model will be greatly improved compared with the conventional Mean Square Error (MSE). Therefore, the loss function is shown in (7).

$$E(\theta) = -\frac{1}{N} \sum_{n} \sum_{q} t_{nq} \log y_{nq}$$  \hspace{1cm} (7)

In (7): $\theta$ is the network parameter; $N$ is the total number of data; $t_{nq}$ is the data label of the actual fault; $y_{nq}$ is the output result of the neural network.

4. Steps for Fault Location of Secondary Equipment Based on DNN

Based on the above, the establishment of a real-time fault location model for secondary equipment includes:

- There may be a small number of error messages during the operation of the smart substation. These error messages do not represent the fault of the secondary equipment. However, if these error messages are not avoided, the fault location function will be frequently activated, increasing the workload of the operation and maintenance personnel. Therefore, to avoid such phenomena, the judgment process of the total number of alarm signals is added to the model. When the background monitoring host detects that the total number of alarm signals is greater than the preset threshold, the fault location module of secondary equipment is activated.

- Retrieve the alarm information detected to form the fault feature set $X_i$.

- Obtain the fault location result by inputting the fault feature set $X_i$ into the pre-trained DNN model and report it to the operation and maintenance personnel.

5. Simulation Analysis

Footnotes should be avoided whenever possible. If required they should be used only for brief notes that do not fit conveniently into the text.

5.1. Introduction to Simulation

To verify the effectiveness of the fault location method proposed in this article, taking a typical smart substation line interval as an example, the topology is shown in Figure 2, and the message information of this interval is shown in Table 3. According to Table 2, there are 16 elements in the abnormal equipment alarm $X_{AEA}$. According to Table 3, there are 13 elements in the abnormal message traffic alarm $X_{AMTA}$, and the abnormal message reception alarm $X_{AMRA}$ has 13 elements. Therefore, the number of neurons in the input layer of the DNN is 42, and the number of neurons in the output layer is the fault type code, which is 8 from Table 4.

| Number | Publish port | Subscribe port | Delivery method |
|--------|--------------|----------------|----------------|
| 1      | Bus MU       | Line MU        | SV             |

Figure 2. Network topology of line interval

Table 3. Line interval Message
| Number | Publish port       | Subscribe port | Delivery method |
|--------|-------------------|----------------|----------------|
| 1      | Bus MU            | Line MU        | SV             |
| 2      | Line MU           | Bus protection | SV             |
| 3      | Line MU           | M&C equipment  | SV             |
| 4      | Line MU           | Line protection| SV             |
| 5      | Intelligent terminal | Bus protection | GOOSE         |
| 6      | Intelligent terminal | Line protection | GOOSE         |
| 7      | Intelligent terminal | Line MU        | GOOSE         |
| 8      | Intelligent terminal | M&C equipment  | GOOSE         |
| 9      | Line protection   | Intelligent terminal | GOOSE         |
| 10     | Bus protection    | Intelligent terminal | GOOSE         |
| 11     | Bus protection    | Line protection | GOOSE         |
| 12     | M&C equipment     | Line MU        | GOOSE         |
| 13     | M&C equipment     | Intelligent terminal | GOOSE         |

Table 4. Line interval Message

| Fault number | Fault code | Fault number | Fault code |
|--------------|------------|--------------|------------|
| 1            | 00000001   | 5            | 00010000   |
| 2            | 00000010   | 6            | 00100000   |
| 3            | 00000100   | 7            | 01000000   |
| 4            | 00001000   | 8            | 10000000   |

5.2. Optimize the DNN model

In the process of training the DNN model, the network is optimized by adjusting the learning rate, the number of hidden layers, and the number of iterations, and the judgment accuracy rate of the training sample set is used as the optimization index of the network parameters. The threshold of the output layer during training is set to 0.6, and the training results are shown in Figure 3-4.

It can be seen from Figure 4 that after 1500 iterations, under various learning rates, the optimization effect of the neural network with 1 hidden layer is the best, the training difficulty of the whole neural network will increase with 2 hidden layers, and the fitting performance of the neural network with 0 hidden layers is weak. It can be seen from Figure 5 that the optimization effect of the neural network is the best when the learning rate is 0.1. Although the convergence speed is faster in the early stage when the learning rate is 0.5, the phenomenon of accuracy rate fluctuation occurs in the learning process, when the learning rate is smaller, the accuracy rate rises slowly, which means the convergence speed of DNN is slower. With the increase in the number of iterations, the accuracy of the neural network will continue to rise, but when the number of iterations reaches a certain value, it will tend to be stable. Because the training speed and resource loss of the model need to be considered in the training process, the inflection point of the rising accuracy is the best when the number of iterations is 2200, and the accuracy of DNN is 98.821%.
5.3. Analysis of simulation results

To study the effectiveness of the DNN fault location model, the proposed DNN method is compared with the conventional fault location method.

5.3.1. Location effect under single fault environment

Take the fault of the DSP module of the merging unit in Figure 2 as an example. After a certain fault occurs, the merging unit sends out an abnormal equipment alarm, a total SV alarm, and a sampling abnormality alarm; due to the wrong sampling information sent by the merging unit, the protection equipment also sends out a total SV alarm and protection (start) DSP sampling error alarm, in addition to the protection being blocked, these feature information will be captured by the adjacent switch. It can be seen from Section II.B that the positioning element of the above information in the feature set $X_{AEA}$ is 1, and the other position elements are all 0. Since there is no message loss or abnormal traffic, the elements in the feature set $X_{AMTA}$ and $X_{AMRA}$ are all 0. Therefore, $X_{AEA}$, $X_{AMTA}$, and $X_{AMRA}$ are shown in formula (8-10) (due to a large amount of data, only non-zero items are listed in some sets).

$$
X_{AEA} = \left[ X_{MU}, X_P, X_{IT} \right]
$$

$$
X_{MU} = [1, ..., 1, ..., 1, ...]
$$

$$
X_P = [0, ..., 1, ..., 1, ...]
$$

$$
X_{IT} = [0, ...]
$$

The fault feature set $X_i$ composed of $X_{AEA}$, $X_{AMTA}$ and $X_{AMRA}$ is used as the input of the DNN, and the output $Y_{DNN}$ calculated by the model trained in the previous section is shown in equation (11).

$$
Y_{DNN} = [0, 0, 0, 0, 0, 0, 0, 1]
$$

According to the fault code in Table 4, the fault type corresponding to (11) is correct.

The conventional fault location method takes literature [8] as an example. Literature [8] uses the SV of the network message analysis device and the double AD sampling value of the protection equipment to compare with each other and analyzes the key message to comprehensively judge the operating state of the secondary circuit. When the DSP module of the aforementioned MU fails, the SV of the network message analysis device will be abnormal, so the result obtained according to the strategy of literature [8] is the fault of the entire protection sampling circuit. According to Table 1 and Table 4, this judgment result corresponding to the fault code mentioned in this article is shown in (12).

$$
Y_{[8]} = [0, 0, 0, 1, 1, 0, 1, 1]
$$
To compare the effects of different methods, this article introduces the relative error between the actual fault range and the suspected fault range as the evaluation index as shown in (13).

\[ Er(\hat{Y}) = \frac{|Y - (Y \cap \hat{Y})|}{|Y|} \quad (13) \]

In (13), \( Y \) is the suspected fault range, \( \hat{Y} \) is the actual fault range. Specify \(|Y|\) as the number of non-zero elements in the set \( Y \).

According to the evaluation index of relative error, the relative error of the DNN model proposed in this article is 0 when the aforementioned sampling module of the MU fails, and the relative error of the method proposed in [8] is 0.75. It can be seen that when this kind of fault occurs, the DNN model can effectively reduce the scope of troubleshooting and improve the efficiency of maintenance by combining multi-dimensional feature information.

According to the above fault location process and relative error evaluation index, for all fault events in the test sample set, the method of DNN and literature [8] is used for fault analysis and error calculation. The final result is shown in Figure 5.

It can be seen from Figure 5 that, compared with the method in [8], the average error and the maximum error of DNN are lower. With the refinement of fault type and fault features, the method in [8] has a poor ability to deal with massive multi-dimensional data. Therefore, the use of DNN can effectively improve the accuracy of the fault location of secondary equipment.

5.3.2. Location effect with unreliable information

Unreliable information refers to the situation where the feature information is wrong or missing in the fault feature set. The following analyzes the fault tolerance of the method proposed in this article in the case of unreliable information and compared with the method in the literature [8].

Taking the fault of port A of the MU in Figure 2 as an example, when the fault occurs, the MU issues the abnormal equipment alarm, the line protection issues the sampling error, and total SV alarm. Since the subscribed messages 1, 7, and 12 are not received, the MU issues the total SV alarm and total GOOSE alarm. The bus protection equipment will fail to receive its subscribed message 2. The M&C equipment will fail to receive its subscribed message 3, the line protection will fail to receive its subscribed message 4, and the traffic of messages 2, 3, and 4 will drop sharply. The positioning element of the above information in the feature set \( X_{AE} \), \( X_{AMTA} \) and \( X_{AMRA} \) are 1, and the rest of the positioning elements are all 0.

If the protection equipment misreports the abnormal equipment alarm at this time, \( X_{AE} \), \( X_{AMTA} \) and \( X_{AMRA} \) are as shown in (14-16).
The fault feature set $X_i$ composed of $X_{\text{AEA}}$, $X_{\text{AMTA}}$ and $X_{\text{AMRA}}$ is used as the input of the DNN, and the output $Y_{\text{DNN}}$ calculated by the model trained in the previous section is shown in equation (17).

$$Y_{\text{DNN}} = \begin{bmatrix} 0, 0, 0, 0, 0, 0, 1, 0 \end{bmatrix}$$

According to the fault code in Table 4, the fault type corresponding to (14) is correct. According to the fault location process in [8], the abnormal equipment alarm of protection equipment belongs to the key information. If this feature information is received, it is determined that there is a fault in the protection sampling circuit. Since the port A of the MU fails at this time, the error between SV of the network message analysis device and the double AD sampling value of the protection equipment exceeds the threshold, so it is determined that the AC sampling circuit of the network message analysis device also has a fault, therefore, the range of suspicious faults is greatly increased. It can be seen that the fault location results in [8] are extremely susceptible to the so-called key information credibility, and cannot maintain good fault tolerance under the condition that the feature information is unreliable.

To discuss whether the proposed method has universal anti-interference ability, 100 sets of samples are selected from the fault set, and these fault samples can obtain correct location results through the above two methods. Randomly set certain feature information in each group of samples to "0" (originally "1") or "1" (originally "0") to simulate the situation where the feature information is not unreliable. Then according to the above process, these samples are sequentially analyzed by DNN and literature [8], and the results are shown in Figure 6.

It can be seen from Figure 6 that in the unreliable situation where the feature information is wrong or lost, the DNN model still has accurate fault location capabilities, and the number of misjudgment samples is much lower than that of the fault location method in [8], and the fault tolerance performance is good. However, it should be screened whether different information confidence levels will affect the judgment results. In the future, information identification links can also be added to eliminate the disturbance of the location results caused by tampering or damage of information during external malicious intrusion [17].

6. Conclusion
Aiming at the problem that conventional methods are difficult to accurately locate secondary equipment faults, this article proposes a smart substation secondary equipment fault location method based on switches and deep learning. Obtain fault feature information by configuring the key alarm
signal capture function and the traffic statistics function on the switch. Based on alarm information, traffic statistics, and message subscription relationships, the characterization method of fault feature information is proposed. Using the deep learning training method, a DNN-based secondary equipment fault location model is established and the fault location steps are given.

The results show that the DNN-based fault location model proposed in this article can handle high-dimensional fault feature sets and accurately locate faults. In the unreliable situation of missing or misreported feature information, the DNN location model has good fault tolerance performance. This is of great significance for reducing the impact of the untrustworthiness of information on fault location in the increasingly complex operating environment of smart substations in the future.

Limited by the lack of theoretical basis for the current deep learning model selection and the shortcomings of the super parameter selection relying on comparative testing, these aspects can be further optimized in the future research process. According to the transfer learning theory, the scope of fault location can be extended to realize the overall fault location of the secondary system of smart substation [18-19].

Acknowledgments
We acknowledge the support from Open Fund of Beijing Key Laboratory of Research and System Evaluation of Dispatching Automation Technology(China Electric Power Research Institute)(No.DZ83-19-005).

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