# RESEARCH ON 5G DIFFERENTIAL PROTECTION CRITERION BASED ON DYNAMIC PATTERN MATCHING ALGORITHM

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*The differential protection of distribution network is realized by using 5G communication, which can greatly reduce the installation and maintenance costs of optical fiber communications. However, the uncertainty of delay and jitter of 5G communication transmission seriously affects the calculation accuracy. A differential protection criterion of distribution network based on the dynamic pattern matching algorithm (DPM) is constructed by calculating the waveform similarity of the measured currents to eliminate the influence of the uncertainty of communication delay and jitter on the criterion result. Then, a deep learning method based on lightweight neural network is proposed to implement the DPM algorithm for reducing the computational time in application. Finally, the correct distinction between internal faults and external faults is realized.*

**Keywords**: 5G; differential protection; DPM algorithm; waveform similarity; communication delay; deep learning

## 1. Introduction

The scale of the distribution network continues to expand, and the complexity of the distributed access of a large number of new energy sources is also increasing, which push the application of differential protection for distribution lines. The differential protection is traditionally realized mainly by using optical fiber communication to compare the current signals. However, it's difficult to achieve wide application of the differential protection technology because of the shortcomings such as high cost and difficult maintenance of optical fiber [1]. Owing to advantages including low delay and high bandwidth [2], 5G communication provides a multi-point to multi-point low-delay data channel for distribution differential protection, and therefore has a broad practical application prospect in the field of differential protection.

Although 5G that is used as a transmission channel for differential protection is characterized by low communication delay, errors occur on the

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timeline during comparison of current, because the data transmission delay at both current sampling points is not completely same. Yuan Tong et al., proposed the application of 5G high-precision time synchronous technology in power grid systems [3]. Although the introduction of time synchronous devices can allow the data to be time-stamped, the higher investment cost of synchronous devices results in difficult promotion of this technology in the distribution network with numerous lines.

Some research have focused on the related fields of differential protection through wireless transmission. Abdel-Latif et al. proposed a method that allowed the data is exchanged through the wireless communication network based on a protection algorithm [4]. Hu et al. put forward a scheme in which real-time communication between distribution network differential protection devices was realized using 5G communication instead of optical fiber communication [5]. However, due to the low delay of 5G communication, the jittering still existed, which influenced the differential protection effect of distribution network [6]. Wu et al. proposed three probability models to assess the impact of communication delays on differential protection, and the mechanism of relay protection malfunction caused by communication delays was introduced in [7]. Although Wu analyzed the risk incurred by excess communication delay to differential protection, he did not give the solution to the problem of excess communication delay [8].

Although application of differential protection through wireless transmission is focused in the above researches, the time tolerance criterion has not been considered. At present, there are Euclidean distance and dynamic time warping (DTW) methods to compare and calculate data waveforms with time error. Euclidean distance is the true distance between two points, or the natural length of the vector. Keogh et al. and Faloutsos et al. respectively proposed the methods of measuring the similarity with Euclidean distance [9-10]. However, the Euclidean distance algorithm is not suitable, because it is only used for time series with the same length and is unable to identify the trend of change and compensate for the delay jitter caused by 5G communication. DTW is a dynamic programming algorithm that calculates the similarity of two time series. It is mainly applied to time series data, such as isolate-word speech recognition, gesture recognition, data mining, information retrieval, etc. WANG et al. proposed application of the DTW algorithm in calculating the differential protection distance [11]. However, because the distance among elements in two time series should be accurately measured according to the DTW algorithm, the calculation is complicated and the time complexity is high. In addition, there are also other methods, such as synchronized measurements [12], the criterion applicable to differential protection based on waveform sinusoidal similarity identification [13], the Discrete Fréchet distance algorithm [14], the Hausdorff distance based restrain criterion [15] etc., which are not suitable for 5G communication.

To this end, this paper studies DPM based 5G differential protection criterion. It improves the deficiencies of the DTW algorithm, and makes up the errors caused by the delay jitter by accurately calculating the similarity of the time series of current sampling at both ends, identifying the trend of change, and compensating for the disturbance on the timeline to a certain extent. Meanwhile, it also overcomes the above-mentioned shortcomings of the DTW algorithm including high complexity, and has a good application value. Besides, we presented a lightweight neural network to reduce the computational time in application.

## 2. DPM-based differential protection criterion

### 2.1. Normalized pre-processing of the current

In order to avoid the impact of different amplitudes of the current on the criterions, it's necessary to pre-process the sampled current in a normalized manner. The amplitude of the current should be compressed to [0,1]. The specific steps are as follows:

Denote the sampled current as $i=\{i_1,i_2,...,i_k,...,i_n\}$, where $k=1,2,...,n$ represents the ordinal number of elements in the current sequence $i$. Take and denote the minimum and maximum values as $i_{min}$ and $i_{max}$ respectively, and put them into the normalization formula:

$$i_k^* = \frac{i_k - i_{min}}{i_{max} - i_{min}} \tag{1}$$

Where, $i_k^*$ is the normalized value of $i_k$. The normalized sampled current sequence is $i^*=\{i_1^*,i_2^*,...,i_k^*,...,i_n^*\}$, where $k=1,2,...,n$ represents the ordinal number of elements in the current sequence $i^*$.

2.2. Introduction to DPM algorithm

There are two known time series $P,Q$, of which the length is $n,m$ respectively. Details are as follows:

$$P=\{p_1,p_2,...,p_i,...,p_n\}$$

$$Q=\{q_1,q_2,...,q_j,...,q_m\}$$

Where, $i$ is the ordinal number in the time series $P$, $i=1,2,...,n$; $j$ is the ordinal number in the time series $Q$, $j=1,2,...,m$.

Select and denote the minimum and maximum values in the time series $P$ as $p_{min}$ and $p_{max}$ respectively. Average the time series $P$, and denote it as $p_{ave}$. If $p_{min} \le p_i < p_{ave}$, $p_i$ belongs to the set A; if $p_{ave} \le p_i < p_{max}$, $p_i$ belongs to set B.

Select and denote the minimum and maximum values in the time series $Q$ as $q_{min}$ and $q_{max}$ respectively. Average the time series $Q$, and denote it as $q_{ave}$. If $q_{min} \le q_i < q_{ave}$, $q_i$ belongs to the set A; if $q_{ave} \le q_i < q_{max}$, $q_i$ belongs to set B.

Calculate the distance among elements in two time series $P$ and $Q$. Specific steps include: list the element values with the length of $n$ and $m$ respectively in the two time series to form the matrix $n \times m$; calculate the distance between every two element values from different series to get $n \times m$ distance values. The calculating formula goes as follows:

$$d_{ij} = \begin{cases} 0; \textit{Two elements belong to the same set} \\ 1; \textit{Two elements do not belong to the same set} \end{cases} \tag{2}$$

Where, $d_{ij}$ is the distance between the $i$th element of P and the $j$th element of $Q$. Fill the distance values $d_{ij}$ obtained above into the corresponding positions of the $n \times m$ matrix network according to their subscripts, where $i$ is the row position and $j$ is the column position.

After that, utilize the DPM algorithm to select a path passing through the above-mentioned $n \times m$ matrix network. Selection of this path should follow the following three conditions:

1) Boundary: the path should start from the lower left corner and end at the upper right corner;
2) Extension: The path should extend all the way to the element that is adjacent or diagonal to the current element in the matrix network.
3) Optimal policy: add up all element values in the matrix network that the path passes through, and select the path with the smallest sum of element values as the optimal path. The sum of all element values passed by this path is the DPM value, denoted as $DPM(P,Q)$.

The DPM algorithm is illustrated as follows:

There are two time series $P = \{3 \quad 6 \quad 3\}$ and $Q = \{6 \quad 3 \quad 2 \quad 1\}$:

**1)** According to the above-mentioned differentiation method, the elements in the time series are categorized into set A and set B. For specific results, see parentheses in Fig. 1;

**2)** Utilize the above-mentioned distance formula to calculate the distance among elements of the two time series. For specific distance, see the numbers in each box in Fig. 1.

**3)** According to the numbers in the boxes, select the shortest path from the lower left corner to the upper right corner. For path direction selected, see the arrow in Fig. 1. The sum of the element values in the matrix network passed by this path is $DPM(P,Q)$.

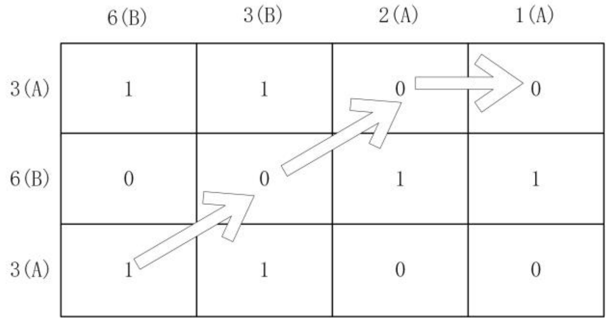



Fig.1 Example of DPM algorithm

### 2.3. Selection of relevant values

#### 2.3.1. Selection of sampling frequency

According to the actual situation of the project, the sampling frequency in this paper is selected as 3000Hz.

#### 2.3.2. Selection of data window length

The length of the data window determines the length of the two sampled current sequences $P$ and $Q$ that are involved in a $DPM(P,Q)$ process. Selection of the length of the data window influences the real-time performance of the final criterion results, and an inappropriate length may affect the correctness of the results. If the length $w$ is too large, the determination process becomes more complicated and the calculation becomes more complicated; if the length $w$ is too small ($P$ and $Q$ are short in length), the two current sequences are short in length with respect to the whole judgment process so that the calculating result is not convincing. In this paper, a data window that is 20ms long is selected in subsequent simulation.

#### 2.3.3. Selection of threshold

The threshold $DPM_{set}$ is the limit value that determines whether to perform the differential protection. Selection of the threshold is directly related to the differentiation between the internal and external faults and the correctness of the determination. Too large threshold affects the timeliness of the results, and too small one may increase the difficulty in distinguishing the internal and external faults. According to the actual situation and based on the sensitivity of the DPM algorithm to similarity, the threshold $DPM_{set}$ is set as zero.

### 2.4. Determination process

In this paper, a line differential protection method based on 5G communication and DPM algorithm is proposed, in which 5G communication connects the current of two lines to be tested, and the DPM algorithm calculates the waveform similarity of the two current sequences. Later, the results are compared with a preset threshold to determine execution of differential protection. The specific determination process is as follows:

**1)** Sample the current at the two nodes of the required differential protection lines; select a data window with appropriate length, in which the current sampled at the two nodes are denoted as $i_1$ and $i_2$, respectively. Then, normalize the sampled current $i_1$ and $i_2$ , and denote them as $i_1^*$ and $i_2^*$ respectively.

**2)** Use the DPM algorithm to measure the similarity distance between $i_1^*$ and $i_2^*$ to obtain $DPM(i_1^*, i_2^*)$;

**3)** Compare the above calculating result $DPM(i_1^*, i_2^*)$ with the preset threshold: if $DPM(i_1^*, i_2^*) > DPM_{set}$, a fault is determined to happen inside the sample space and the differential protection is performed; if $DPM(i_1^*, i_2^*) \le DPM_{set}$, a fault outside the sample space is determined and no differential protection is performed.

**4)** In order to realize uninterrupted detection of the differential protection position of the distribution network, it is necessary to guarantee the continuity of the data within a certain period of time, and select the next data window on the basis of the current data window. This is done by: taking the last $m$ current values of the current data window as the first $m$ current values of the next data window, and the last $(n-m)$ current values of the next data window as the new sampled current values. The above method allows continuous updating of the current sequence in the data window so that a new current sequence can be obtained. Run the DPM algorithm again to determine whether to perform the differential protection. Repeat this process continuously.

See Fig. 2 for the flow chart of differential protection criterion.

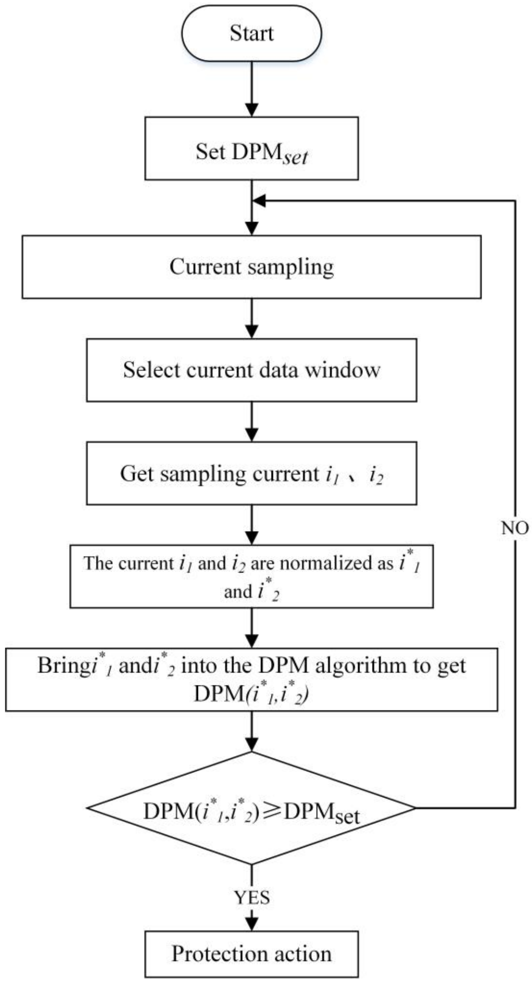



Fig.2 Flow chart of differential protection

### 2.5. Implementation of the DPM through deep learning

To reduce the computational time in the application, in this subsection, we present a deep learning method based on lightweight neural network to implement the DPM algorithms. The lightweight neural network takes the normalized sampling currents, $i_1^*$ and $i_2^*$, as input, and takes the result computed by DPM as output. Fig. 3 shows the structure of the proposed lightweight neural network.

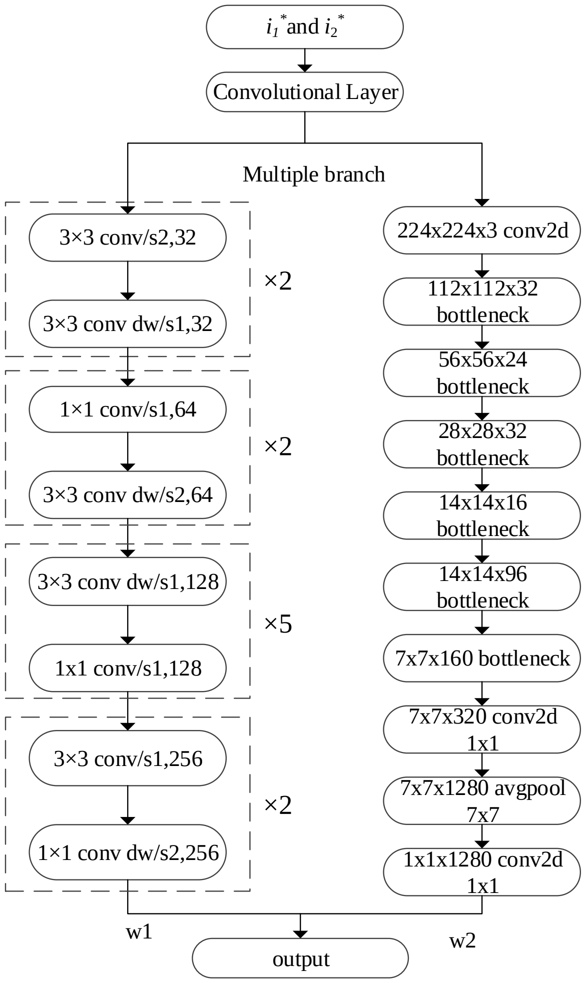



Fig. 3 Structure of the proposed lightweight neural network for implementing DPM

As shown in Fig.3, two branches of neural network model are constructed. The left-hand neural network includes several 3x3 and 1x1 convolution blocks. Besides, the right-hand neural network composed of bottleneck layer and convolution layer. The residual structure is introduced to enhance the propagation of gradient. Finally, the multiple branch network is constructed by the above two models, and the input of the data model is transformed into array data through convolution layer, which are respectively input into the constructed model, and the predicted value is output to the decision layer.

## 3. Simulation verification

The determination method proposed above is verified in this paper by line simulation and actual 5G communication. Two communication nodes (node 1, node 2) are used to transmit current data, and the current sampled at node 1 is transmitted to node 2 through the 5G base station to complete the simulation of theoretical 5G communication delay. By Python, a distribution network model is set up to simulate the actual differential protection lines, and the lightweight neural network for implementing DPM is built to reduce the computational time. The current data received at node 2 is sent to the node1. Then, the DPM algorithm is operated. Lastly, current data and the result obtained by DPM is used to train the neural network model.

### 3.1. Simulation scenario

Fig. 4 gives the scenario mentioned in this paper. During normal operation, it can be powered by either single or dual power supply. The differential protection of the lines between A1 and A2 is hereby studied.

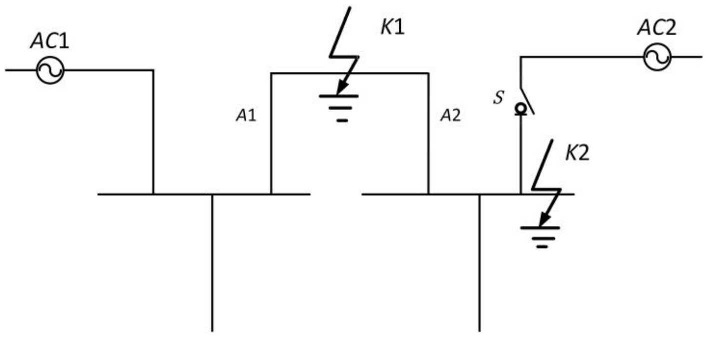


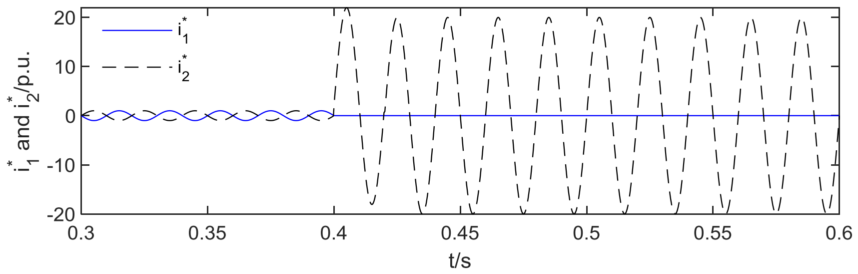
Fig.4 Simulation model

### 3.2. Simulation analysis

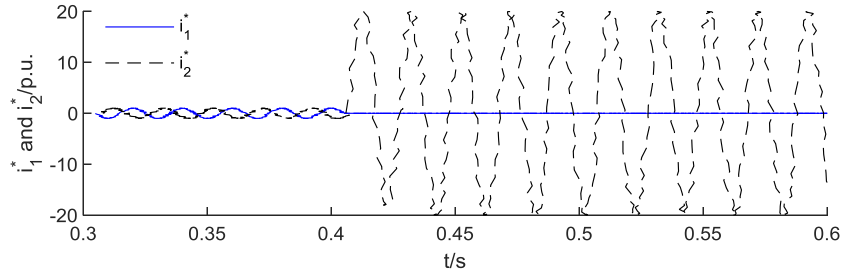
#### 3.2.1. Internal faults supplied by the single-side power supply

The distribution network structure shown in Fig. 4 is adopted. Disconnect the switch S to realize the single power supply. At 0.4s, the A-phase ground fault occurs at point K1 between A1 and A2. Take the current measured at A1 as $i_1$, and the current measured at A2 as $i_2$. Substitute them into the normalization formula to get the normalized currents, which are then denoted respectively by $i_1^*$ and $i_2^*$, as shown in Fig. 5(a). The delay waveform after 5G transmission is shown in Fig. 5(b). In the data window that is 20ms long, the similarity distance between the two current sequences is measured. As shown in Fig. 5(c), the trained lightweight neural network obtained the DPM value as time goes by. It can be seen from the figure that when t = 0.4398s, $DPM(i_1^*,-i_2^*) > DPM_{set}$ (take the negative value because $i_1^*$ is reverse to $i_2^*$). Thus, the differential protection is performed. Besides, adopting the DPM algorithm, when t = 0.4659s,

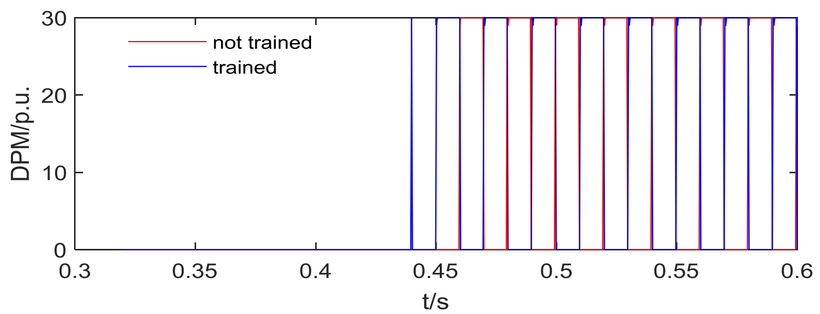
$DPM(i_1^*, -i_2^*) > DPM_{set}$. Therefore, we could get the conclusion that, the trained lightweight neural network could reduce the computational time comparing the DPM algorithm.




(a) Standardized current waveform




(b) Standardized current time delay waveform

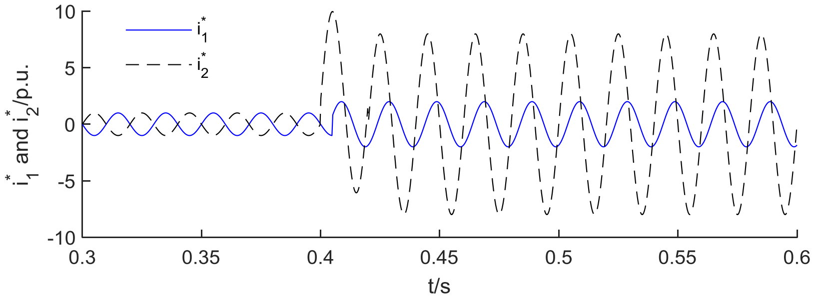



(c)DPM values

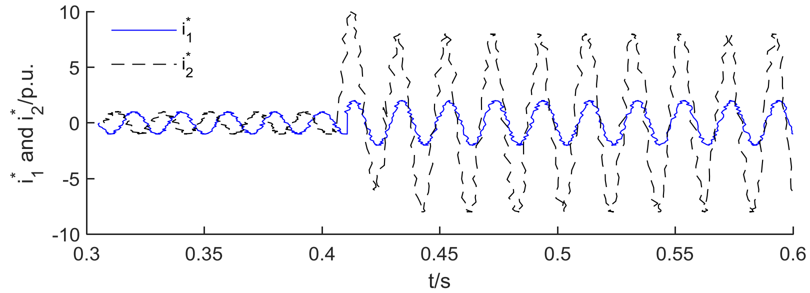
Fig.5 Simulation analysis of internal faults supplied by single side power supply

### 3.2.2. Internal faults supplied by the single-side power supply

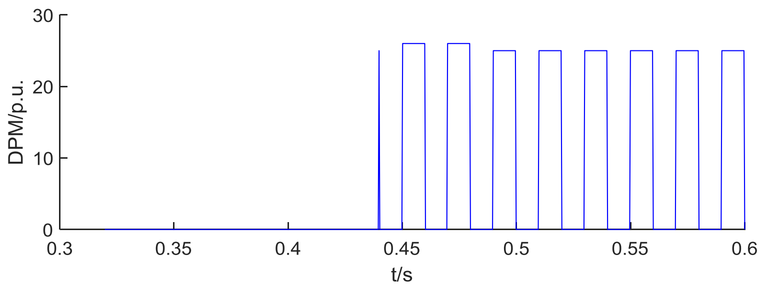
The distribution network structure shown in Fig. 4 is adopted. Close the switch S to realize the two-side power supply. At 0.4s, the A-phase ground fault occurs at point K1 between A1 and A2. Take the current measured at A1 as $i_1$, and the current measured at A2 as $i_2$. Substitute them into the normalization formula to get the normalized currents, which are then denoted respectively by $i_1^*$ and $i_2^*$, as shown in Fig. 6(a). The delay waveform after 5G transmission is shown in Fig. 6(b). In the data window that is 20ms long, the similarity distance between the two current sequences is measured with the DPM algorithm. As shown in Fig. 6(c), the trained lightweight neural network obtained the DPM value as time goes by. It can be seen from the figure that when t = 0.4398s, $DPM(i_1^*,-i_2^*)>DPM_{set}$ (take the negative value because $i_1^*$ is reverse to $i_2^*$). Thus, the differential protection is performed.




(a) Standardized current waveform




(b) Standardized current time delay waveform

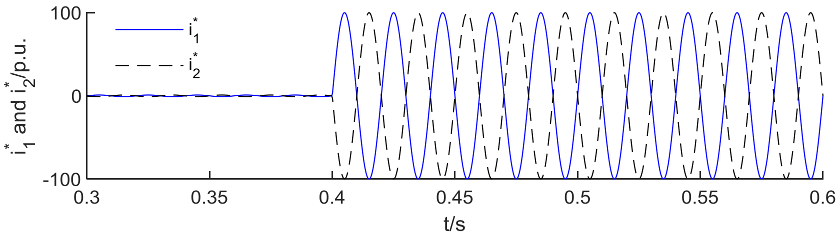



(c)DPM values

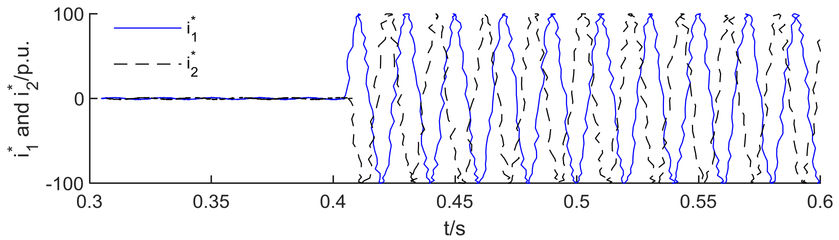
Fig.6 Simulation analysis of internal faults supplied by two side power supply

### 3.2.3. External faults supplied by two side power supply

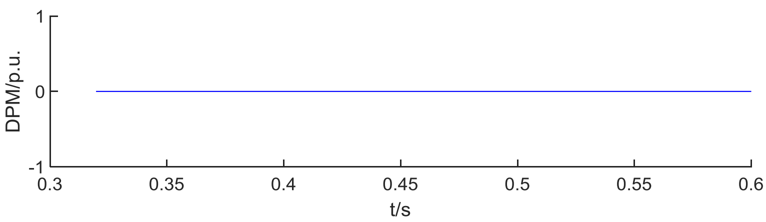
The distribution network structure shown in Fig. 3 is adopted. Close the switch S to realize the two-side power supply. At 0.4s, the external ground fault occurs at point K2. Take the current measured at A1 as $i_1$, and the current measured at A2 as $i_2$. Substitute them into the normalization formula to get the normalized currents, which are then denoted respectively by $i_1^*$ and $i_2^*$, as shown in Fig. 7(a). The delay waveform after 5G transmission is shown in Fig. 7(b). In the data window that is 20ms long, the similarity distance between the two current sequences is measured with the DPM algorithm. As shown in Fig. 7(c), the trained lightweight neural network obtained the DPM value as time goes by. It can be seen from the figure that after an external fault happens, DPM value keeps unchanged and does not exceed the threshold. Thus, no differential protection is performed.




(a) Standardized current waveform




(b) Standardized current time delay waveform




(c)DPM values

Fig.7 Simulation analysis of external faults supplied by two side power supply

Finally, the above three examples show that the algorithm can distinguish the internal and external faults of the distribution system accurately. At the same time, the deep learning method based on lightweight neural network is used to realize the algorithm, which can reduce the calculation time in the application and improve the practicability of the algorithm.

## 4. Conclusions

Problems with differential protection of distribution network using 5G communication instead of traditional optical fiber, such as low delay and jitter, etc., can be solved by a DPM algorithm, which has a tolerance of jitter on the time axis. It compensates for the errors caused by low delay and jitter to eliminate their influence on the criterion result. By constructing a distribution network differential protection criterion based on the DPM algorithm, the correct distinction between internal and external faults is realized. At the same time, the deep learning method based on lightweight neural network could reduce the computational time in application. Finally, the results of simulation verify the correctness of the distribution network differential protection method proposed in this paper.

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