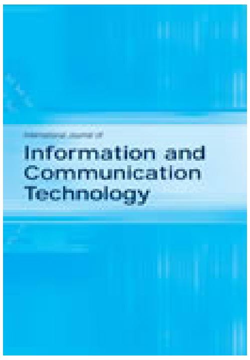

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An accident chain-based risk assessment method for power system faults

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Abstract: A chain fault risk assessment method based on transformer-federation migration learning algorithm is proposed. Firstly, this paper describes the chain fault evolution path of AC-DC hybrid grid, constructs fault simulation model, and clarifies the selection principle of the initial fault set of the accident chain. Secondly, the chain fault probability assessment model based on the accident chain is established according to the key indicators of the accident chain. Then, the weighted fuzzy C-mean clustering algorithm is used to cluster and analyse the correlation indicator values, and the fault set feature extraction module is obtained according to the transformer model. Finally, a multimodal transformer architecture based on federated learning cooperative work is designed to realise the accurate estimation. The experimental results show that the proposed method for AC-DC hybrid grids has a good generalisation capability and can quickly and accurately determine the fault set feature extraction module.

Keywords: AC-DC hybrid grid; accident chain; transformer model; federated migration learning; fault analysis; risk assessment.

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1 Introduction

AC-DC hybrid grids are more advanced than traditional grids in connecting regions, especially in the area of long-distance transmission. To meet the demand of power consumption of various users in various regions and further solve the problem of load and energy balance, the expansion of AC-DC hybrid grids has become an inevitable trend (Wu et al., 2023; Biglarahmadi et al., 2021; Liu et al., 2021). AC-DC hybrid grids are more complex than traditional grids, and when a fault occurs, it affects a wider area and causes greater losses (Feng et al., 2024b). It is particularly important to develop more sensitive, accurate and reliable fault diagnosis techniques for power grids.

AC-DC hybrid grid has its unique structural and operational characteristics, to meet the demand for long-distance and large-capacity power transmission, but also to the safe and stable operation of the grid has brought a serious challenge, the chain reaction of local faults in the grid evolves into the possibility of global security risk is increasing (Galvez and Abur, 2023; Mirsaeidi et al., 2024; Zhu et al., 2023; Li and Chi, 2024). It is undoubtedly great realistic significance and theoretical value to study the chain fault evolution characteristics of large-scale grids and carry out chain fault risk assessment.

Grid fault diagnosis is to evaluate the correctness of the protection action by analysing various electrical and switching information in the system to identify the position of the faulty equipment, the time of failure, the fault type and the cause of the fault. In Panahi et al. (2021), mathematical models of overhead line and DC network configuration are built to realise the precise positioning of DC network faults. In Feng et al. (2024a), a distance topology matrix is introduced to fit the topology of the LV distribution network, and a random fractal search is used to find an optimised model based on stochastic fractal search to support fault identification in distribution networks. In Xie et al. (2025), taking into account the diverse information perturbation elements and based on the cast function of interphase short-circuit fault current characteristics, an information-physical system module for a power distribution network is constructed for serving the grid state detection. In Shetwan et al. (2025), targeting gas turbine systems in the system, the failure mode and effects analysis (FMEA) is combined with the decision testing and evaluation laboratory (DEMATEL) model to determine the priority of critical faults. In Sonawane et al. (2023), establish reliability modelling based on fault tree analysis (FTA) method to analyse the probability of component failures in large-scale photovoltaic systems.

Establish reliability modelling based on FTA method to analyse the probability of component failures in large-scale photovoltaic systems.

However, it is necessary to see that the traditional fault analysis methods mostly use physical modelling to construct grid state models and fault libraries, and much data models need to be introduced into the research process. The hybrid AC-DC grid is more complex than the traditional grid network architecture, and the operating conditions are more diverse, so it is difficult to achieve accurate fitting of the traditional physical model, and there is the problem of low generalisation ability.

In 2003, after three 345 kV transmission lines in Ohio, USA, tripped due to short circuits caused by contact with trees, the system failed to clear the fault in a timely manner, leading to load transfer and triggering a chain reaction. Subsequently, a number of power plants were taken out of operation due to mis-operation of protection systems or human misjudgement, eventually resulting in a large-scale collapse of the North American power grid. This was because traditional assessment methods are based on a single fault mode. The causal chain – trees coming into contact with the lines, causing protection mis-operation, which in turn led to load transfer and eventually voltage collapse – was not incorporated into the assessment system. In 2012, after the northern power grid in India collapsed due to equipment overload and mis-operation of protection systems, the eastern and northern power grids collapsed again during the recovery process because various states consumed electricity beyond the planned amount and failed to effectively implement dispatching instructions, resulting in power outages in nearly half of the country. This was because traditional risk assessment systems did not fully consider the coupling relationships between cross-regional power grids. However, the method proposed in this paper has strong generalisation ability and takes into account the impact of many factors on the probability of risk occurrence.

In nearly years, the new generation of artificial intelligence technology has been fast developing, through the method named as offline training and online recognition, it can quickly finish the tasks such as prediction, classification, etc., especially the deep learning technology shows more application potential by virtue of its powerful learning ability (Zhang et al., 2024). In Wang et al. (2024), a deep learning-based smart grid fault diagnosis and recovery strategy is proposed, which reduces the disturbing factors in the study of fault diagnosis and recovery strategies and improves the accuracy of fault diagnosis and recovery. However, too much emphasis is placed on the examination of fault diagnosis and recovery strategies, which leads to the selection of its indexes being prone to irrationality. In Wu (2023), real-time diagnosis of grid faults was achieved by constructing a visualisation technique based on a deep classification model, which improved the feature extraction efficiency, fault recognition rate, and visualisation efficiency, and shortened the prediction time, but the interpretability of the modified algorithm was weak. In Jiang et al. (2022), an adaptive grid feature extraction method for insufficient labelling data is proposed, and the designed grid fault diagnosis method has good pattern portability and robustness. However, the case of protection faults such as grid protection system refusal and mis-operation is ignored. Utilising deep learning techniques to mine the intrinsic connection of grid model state data and establish mapping can improve the speed of online identification of critical lines, which is crucial in practical applications. In Alhanaf et al. (2023), a fault analysis model is constructed based on one-dimensional convolutional neural networks (1D-CNN), taking into account the voltage and current data in the network. In Alhanaf et al. (2024), the 1D-CNN model is optimised based on long short-term memory networks (LSTM) to achieve the state estimation of the power grid and improve the reliability of power grid operation. In (Gokulraj and Venkatramanan, 2024), the LSTM model and convolutional neural networks (CNN) are fused and introducing gradient boosting machines (GBM) to solve the network structure heterogeneity problem in microgrid fault analysis.

However, the above data-driven methods have limitations in practical power system applications. Chain faults in the power system have obvious before and after causal correlations, and it is necessary to systematically analyse the cause and effect of faults and construct a chain fault analysis model. At the same time, there is noise interference during physical quantity acquisition, transmission, and interaction in AC and DC networks, which is seldom mentioned in previous work, limiting the application of the model in real-world scenarios.

In the face of complex AC-DC grid architecture, many existing methods have insufficient generalisation ability to effectively detect line faults. For this reason, this paper fuses the accident chain model and deep network model to propose an optimisation-enhanced risk assessment method for power system chain faults. The innovative points are as follows:

1 According to the accident chain model to fit the fault chain effect of AC and DC system, and using the weighted fuzzy C-mean clustering algorithm on the network structure index and grid operation index collection, to construct a complete and reliable fault state analysis model.

2 Based on the fault analysis model, the federal learning mechanism is used to optimise the design of the Transformer model to strengthen the global analysis capability of the fault diagnosis model data, enhance the model generalisation capability, and meet the needs of grid state analysis of actual complex AC-DC hybrid grids.

2 Analysis of interlocking faults in AC-DC hybrid grids

2.1 Chain fault analysis

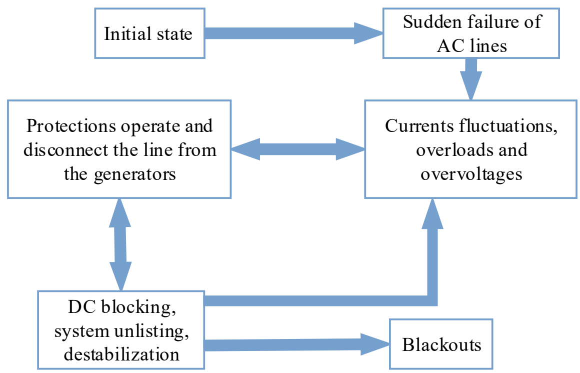
An accident chain refers to a process in which a series of events or factors interact, leading to the development of an accident. Once a major accident occurs in an AC/DC hybrid power grid, it may result in large-scale power outages, affecting the economy, social order, and security. Therefore, preventing the formation of accident chains is crucial for improving system reliability, reducing economic losses, and ensuring public safety.

The AC-DC hybrid grid chain fault evolution path consists of three parts, which are the primary state, the developmental state, and the deterioration state. The evolution pattern and dominant factors between each stage are shown in Figure 1. A sudden fault in a DC line is the initiating event, and its absolute probability of occurrence is based on historical data or expert evaluation. Power flow fluctuations, overloads, and overvoltages are the propagation processes, and their probabilities of occurrence after the occurrence of a preceding event are determined by system parameters. Protection actions, line disconnections, generator and DC blocking, system splitting, and instability are intermediate events, while large-scale power outages are the final result. The propagation processes and intermediate events interact with each other, and in severe cases of faults, they will lead to the final result.

Faults under the initial phase are mainly caused by a chance event, such as accidental line breakage or short circuit faults due to environmental and other factors. Most of them are general line faults, so the impact of faults under this phase is usually within the controllable range (Gokulraj and Venkatramanan, 2024; Huang and Xia, 2022; Zhang et al., 2022; Ma et al., 2022).

After an initial fault occurs, it may lead to a shift in the current, further causing problems such as overloading and voltage fluctuations in the neighbouring lines. In the case of low line current margins, forced outages may occur due to sudden increases in current pressure. Furthermore, the development stage of AC-DC hybrid grid chain faults generally shows medium- to long-term characteristics and is mainly affected by grid current and voltage. Effective control measures can in principle inhibit the rapid spread of interlocking faults (Dai et al., 2023; Sun et al., 2020).

Figure 1 Evolution pats of interlocking faults (see online version for colours)

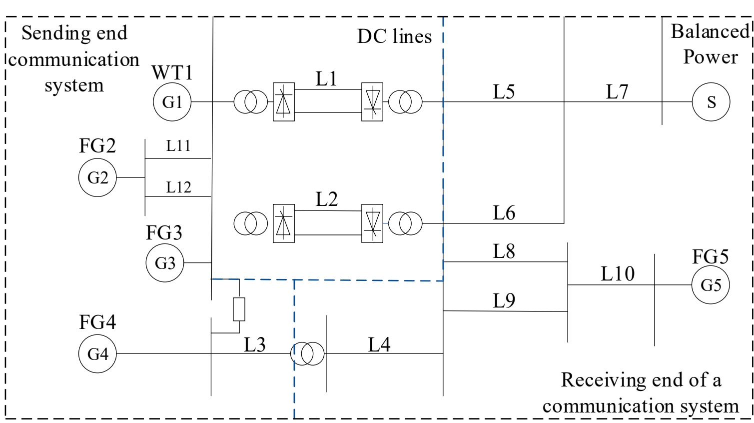


When the chain fault evolves to the deterioration stage, it will involve the core equipment such as DC converter station, and its impact on it is serious. For example, the voltage reduction in the near-area of the fault causes phase change troubles at the converter station, and further successive phase change failures may lead to DC blocking. Additionally, transient overvoltage will occur in the near-area due to the reactive power surplus problem, which will cause a huge impact on the voltage-sensitive equipment. After a large number of AC line outages and DC blocking problems occur one after another, there is a serious power imbalance, which further triggers the grid voltage-frequency collapse (Zheng et al., 2021; Deng et al., 2021).

2.2 *Fault simulation model*

Based on the actual situation project and working condition of new energy grid-connected operation, the grid fault simulation model shown in Figure 2 is built in PSCAD/EMTDC, where WT is the wind turbine, FG is the thermal generator, and L is the line.

Figure 2 Fault simulation model



In the AC-DC hybrid grid topology diagram, G1 is a doubly-fed wind turbine, and G2, G3, G4, and G5 are thermal generating units, respectively. And, a 12-pulsation thyristor converter is used as the DC line converter. The parameters of lines and gensets are shown in Table 1.

Table 1 Parameters of grids

	Parameter	*Value*
Line	Feeder AC system voltage rating/kV	345
	Rated AC system voltage at the receiving end/kV	230
	AC line positive sequence negative sequence impedance/($\Omega \cdot m^{-1}$)	6.21×10^{-5}
	AC line positive sequence negative sequence reactor/ ($\Omega \cdot m^{-1}$)	4.0019×10^{-4}
	AC line positive sequence negative sequence capacitance/($kV \cdot (M\Omega \cdot m)^{-1}$)	391.56
	AC line zero sequence resistance/($\Omega \cdot m^{-1}$)	3.19×10^{-4}
	AC line zero sequence reactance/($\Omega \cdot m^{-1}$)	1.1085×10^{-3}
	AC line zero sequence reactance/($kV \cdot (M\Omega \cdot m)^{-1}$)	535.17
Generator sets	G2, G3 generator capacity/MVA	2,000
	G4, G5 generator capacity/MVA	500
	Rated DC voltage/kV	500
	Rated DC current/kA	2

3 Evaluation model based on the probability of interlocking faults in the accident chain

3.1 Selection of initial fault set

The initial faulty branch is selected based on the principle that no serious faults are omitted and as much as possible the less serious faults are screened out. The initial risk value of a defined branch is composed of the branch failure probability, the original load factor, the original trend proportion of the branch, and the trend change in other branches after the branch opens and closes in the system. Among them, the branch failure probability $P_{Li,0}$ is mainly affected by factors such as the operating life of the branch and the natural environment. It is worth stating that, in order to simplify the chain fault analysis model, the default grid is in the same geographic and meteorological environment and has the same number of years of operation. Therefore, it can be considered that the fault probability $P_{Li,0}$ is proportional to the length of the branch.

The value normalised to the length of all branches in the whole network as the probability of failure of a branch can be expressed as:

$$P_{Li,0} = \frac{L_{L_i}}{\sum_{j \in \Omega} L_{L_j}} \tag{1}$$

where L_{Li} is the branch L_i length and Ω is the set of all branches of the grid.

The initial load factor can be expressed as:

$$D_{Li,0} = \frac{F_{Li,0}}{F_{Li.\max}} \tag{2}$$

where $F_{Li,0}$ and $F_{Li,\max}$ are the initial tidal current value and thermal stability limit value of the branch circuit L_i, respectively.

This indicator can be expressed as:

$$W_{Li,0} = \frac{F_{Li,0}}{\sum_{j \in \Omega} L_{L_{i,0}}} \tag{3}$$

Indicators of changes in tidal currents in other branches caused by branch openings:

$$E_{Lj,0} = \sum_{L_j \in \Omega, j \neq i} \frac{\Delta F_{Lj}}{F_{Lj,0}} \tag{4}$$

where ΔF_{Lj} is the amount of current change of branch L_j, and $F_{Lj,0}$ is the initial current of branch L_j. The larger the value of this index indicates that the larger the amount of network-wide current transfer caused by the opening of the branch L_i, the greater the impact on the power grid.

Therefore, the initial risk value of the branch is defined as:

$$R_{Li,0} = P_{Li,0} \cdot D_{Li,0} \cdot W_{Li,0} \cdot E_{Lj,0} \tag{5}$$

3.2 Analysis of indicators

By analysing the structural metrics and operational metrics, it is possible to screen and identify the important branches in the system. The structural metrics mainly include the tidal median and the electrical structure importance (Huang et al., 2022).

The tidal median is usually used to measure the importance of nodes or branches in a complex network. It is difficult to measure the importance of grid branches by ordinary topology metrics, therefore the importance of lines is weighed by the line tidal median metric $\alpha_{ij,mn}$. The higher the tidal median, the more important the line is in the system. The index can be expressed as:

$$\alpha_{ij,mn} = \min\left(S_m, S_n\right) \frac{P_{ij}(m, n)}{P_{mn}} \tag{6}$$

where P_{mn} is the active power from G_m to load node L_n, $P_{ij}(m, n)$ is the active power from generator G_m on branch ij to load node L_n, and $\min(S_m, S_n)$ is the smaller value of the actual output of generator G_m and load L_n.

The electrical connectivity is defined as the sum of the equivalent impedance of each branch and the electrical structure importance is shown in equation (7). The higher the electrical structure importance, the lower the amount of acceptable current transfer of the branch in the grid structure, and the higher the impact on the power system when the branch l is disconnected. Then the higher the importance of the branch l (Ruan et al., 2025).

$$\begin{cases} Z_G = \sum_{i=1}^{N}\sum_{j=i+1}^{N}\left[\left(Z_{ii}-Z_{ij}\right)-\left(Z_{ij}-Z_{jj}\right)\right] \\ \Delta Z_G^{(l)} = \dfrac{Z_{G-l}-Z_G}{Z_G} \end{cases} \tag{7}$$

where Z_{ii}, Z_{ij}, Z_{jj} are the entries of row i, column i, row i, column j, and row j, column j of the node impedance matrix, respectively, $\Delta Z_{(l)}^{G}$ is the electrical structural importance of branch l, and $Z_{G\text{-}1}$ is the degree of electrical connectivity of branch l after it is disconnected.

Operational indicators mainly include hazard indicators, voltage fluctuation Terre entropy. The danger index λ_d can be constructed as shown in equation (8). It can reflect the safety level of each branch after the initial line disconnection, and the large λ_d.

$$\begin{cases} \omega_d = \min \dfrac{\left|Z_d - \dfrac{Z_1+Z_2}{2}\right|}{\left|\dfrac{Z_1+Z_2}{2}\right|} \\ \lambda_d = \dfrac{1}{\omega_d} \end{cases} \tag{8}$$

where Z_d is the measured impedance and Z_1 and Z_2 are the positive and negative direction rectified impedances of the offset characteristic impedance relay, respectively.

The voltage fluctuation Terre entropy E_{Uf} index is used to indicate the influence of the branch on the system voltage after the initial line disconnection, and the bigger the E_{Uf} is, the bigger the influence of the voltage fluctuation on the system after the branch is disconnected.

$$\begin{cases} \Delta V_{i(l)} = \left|V_{i(l)} - V_{i(0)}\right| \\ \mu_{i(l)} = \dfrac{\Delta V_{i(l)}}{\sum_{i=1}^{N}\Delta V_{i(l)}} \\ E_U = \sum_{j=1}^{N_k}\left(\dfrac{\mu_{kj}}{\mu_k}\right)\ln\left(\dfrac{\mu_{kj}\cdot N_k}{\mu_k}\right) \\ E_{Uf} = E_{1U}+E_{2U} = \sum_{k=1}^{K}\left(\dfrac{\mu_k}{\mu}\right)E_U + \sum_{k=1}^{K}\left(\dfrac{\mu_k}{\mu}\right)\ln\left(\dfrac{\mu_k\cdot N}{\mu\cdot N_k}\right) \end{cases} \tag{9}$$

where $V_i(0)$ and $V_i(1)$ are the initial voltage of node i and the voltage of node i after line l is disconnected, respectively, N is the number of nodes in the power system, and K is the number of node voltage levels; within voltage level k, N_k is the number of nodes, μ_k is the sum of voltage volatility, μ_{kj} is the voltage volatility of node j, and E_U is the voltage volatility variability; E_{1U} is the voltage volatility variability within the voltage level, E_{2U} is the voltage fluctuation rate variability between voltage levels, μ is the sum of voltage fluctuation rates of the system, E_{Uf} is the total voltage fluctuation rate variability of the system.

Since chained faults have a clear before-and-after causal correlation, faults can be categorised after calculating the correlation index value in each round. It is worth stating that the subject of this paper is chain faults, i.e., the focus is on the class of branches with the highest correlation.

The weighted fuzzy C-means clustering algorithm (WFCM) is employed to cluster relevance indicators values in this paper. The algorithm is simple in design and assigns different weights to the sample points to emphasise their different effects on the classification, which provides strong robustness facing noise and outlier interference and good classification results (Wang et al., 2023). The WFCM objective function can be written as:

$$\lambda = \min\left\{\sum_{j=1}^{a}\sum_{i=1}^{b}\alpha_{ij}^{c}\beta_i d_{ij}^2\right\} \tag{10}$$

where a is the number of samples, b is the number of clustering centres, α_{ij} is the degree of affiliation of sample j belonging to the i^{th} clustering centre, d_{ij} is the distance between sample j and the i^{th} clustering centre; c is the fuzzy weighted index, β_i is the sample weight, which in this paper is taken as the ratio between the inverse of the distances between the sample point and the other samples and the inverse of the distances between all sample points and the sum of the distances.

Based on the Lagrange multiplier method the WFCM affiliation matrix and clustering centre iteration formula can be derived as:

$$\alpha_{ij} = \frac{1}{\sum_{m=1}^{b}\left(d_{ij} / d_{im}\right)^{\frac{2}{c-1}}} \tag{11}$$

$$\gamma_j = \frac{\sum_{i=1}^{a}\beta_j\alpha_{ij}^{m}x_i}{\sum_{i=1}^{a}\beta_j\alpha_{ij}^{m}} \tag{12}$$

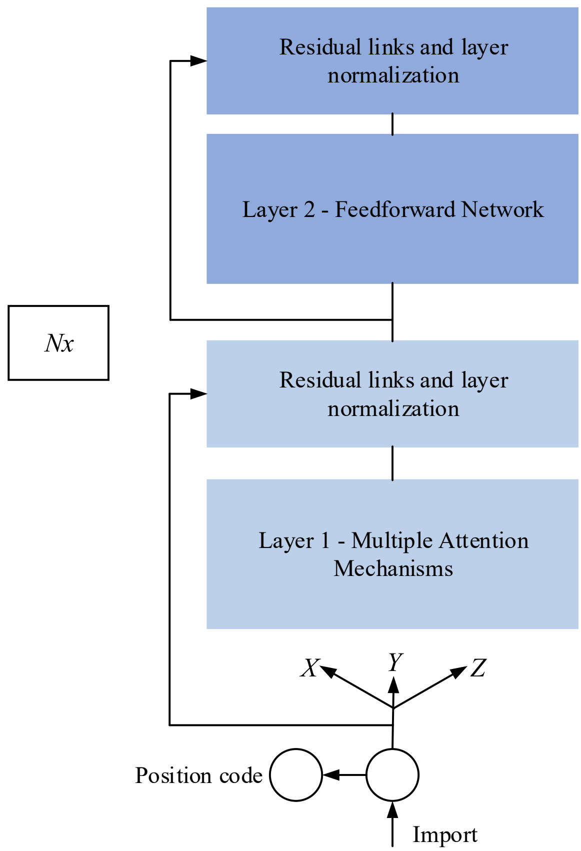
where γ_j is the clustering centre and x_i is the data to be classified.

4 Evaluation of fault methods based on transformer-federation migration learning

4.1 Feature extraction module for transformer

The original fault data is defined as $L = \{L_1, L_2, L_3, \ldots, L_N\}$, and the dimensionality reduction of the data L is realised by principal component analysis, which downgrades the three-phase current data and the zero-sequence current data to one dimension to extract the L^P features associated with the fault data as a whole, and the downgraded data is defined as $L^P = \{L^{P1}, L^{P2}, L^{P3}, \ldots, L^{PN}\}$, which is the input layer data of the transformer mode. In addition, the labels of the fault data are defined as $i = \{i_1, i_2, i_3, \ldots, i_N\}$, where $ij = [i_1^j \quad i_2^j \quad i_3^j]$, and the identified labels can be processed by one-hot coding.

Figure 3 Encoder model structure (see online version for colours)



The Transformer model consists of two parts, encoder and decoder (Shu et al., 2025). The TTHNN-SA model uses the Encoder part of the Transformer model for feature extraction of fault data (Xu et al., 2023; Han et al., 2021). In Figure 3, the structure of encoder model is given. The dimensionality reduced data is represented as vectors by positional encoding. The first layer of the Encoder is a multi-head attention mechanism (multi-head) and the second layer is a feedforward neural network (FNN). Both layers have a residual connection followed by layer normalisation. The input to the self-attention mechanism is the output encoded by positional encoding packed into a matrix. This matrix is then linearly transformed three times using three pre-trained matrices W^X, W^Y, W^Z. Further, the query matrix X, the key matrix Y, and the value matrix Z are determined. The formula for the self-attention mechanism can be expressed as:

$$H = A(W, Y, Z) = soft\max\left(\frac{XY^T}{\sqrt{l_y}}\right)Z \tag{13}$$

where l_y is the dimension of Y. The multi-head attention mechanism is able to define multiple sets of W^X, W^Y, W^Z, and calculate different X, Y, Z by different W^X, W^Y, W^Z. The n results of the self-attention mechanism are then spliced together to get the final result $H = \{H_1, H_2, H_3, \ldots, H_N\}$, which is input into the second layer of the feedforward network after residual concatenation and layer normalisation. The FNN consists of two linear transformations and Relu activation function and the computational formula can be expressed as:

$$Q = W_2 \operatorname{Re} LU\left(W_1 x + b_1\right) + b_2 \tag{14}$$

where W_1 and W_2 are the weight matrices of the linear transformation, b_1 and b_2 are the bias parameters. The post output of the feed forward network is normalised by residual linking and layer normalisation to get the final output.

4.2 Federated migration learning mechanisms

In order to strengthen the generalisation ability of fault identification model, enrich the fault data samples, introduce the federal migration learning mechanism to expand the training volume of working condition data, fully explore the potential features of operation data, improve the feature extraction ability of transformer model, and effectively support the safe operation of complex AC-DC marriage power grid.

The design of a transformer-based multimodal federated migration learning framework enables the integration of migration methods to enhance the model's performance in global personalisation tasks. When designing a multimodal transformer architecture based on federated learning collaborative work, the complexity of various data modalities needs to be considered and the specific needs of each participant need to be met (Oh and Lee, 2024; Wu et al., 2024).

In this paper, in order to determine the multimodal transformer architecture, the data of various modalities need to be segmented and mapped linearly. The segmented data is converted into a uniform vector representation. In addition, the linear mapping results containing the modal information vectors are utilised and arranged in the original sequence to form a sequence of processed data fragments (Li et al., 2024). It should be noted that in order to cope with the inconsistency of data fragment sizes among different modalities, the architecture designs specific mapping matrix sizes for different modalities to ensure the length consistency of the resultant vectors after linear mapping. The linear mapping matrices for different modalities have different numbers of rows and the same length as their modal data fragments. In addition, these linear matrices have the same number of columns, which ensures that data fragments of different data modalities have the same length after linear mapping, which is conducive to the unified processing of the transformer model.

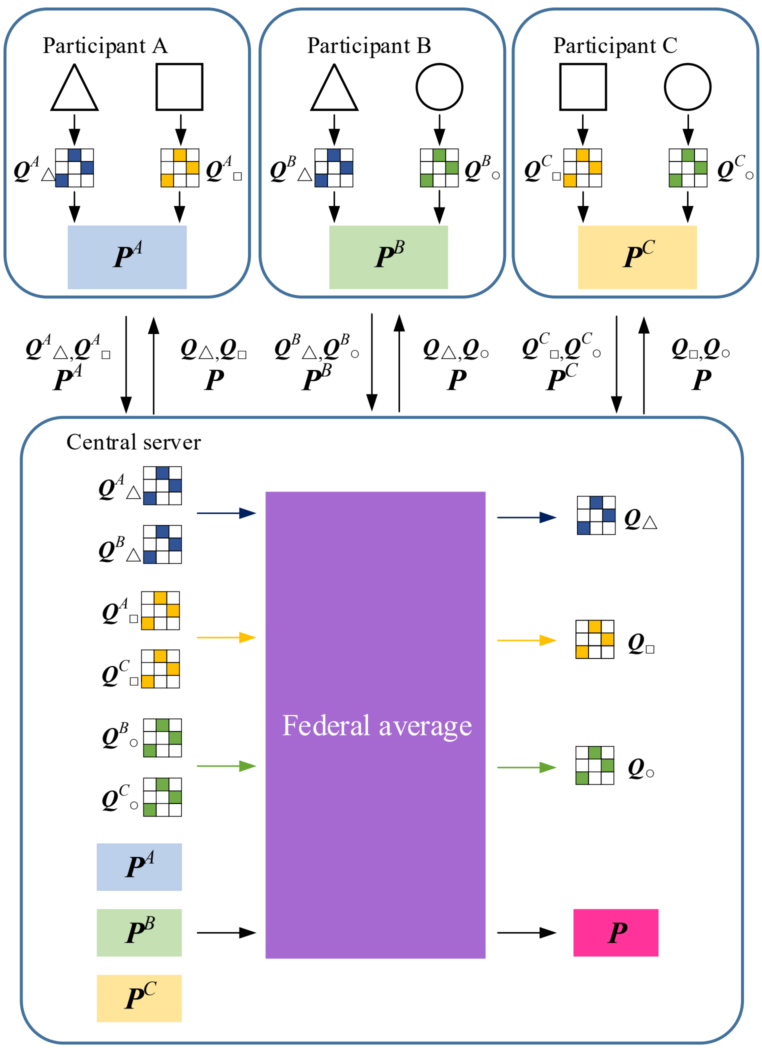
The parameter optimisation in the framework is mainly divided into:

1. Optimisation for linear mapping and modal embedding parameters. It covers linear transformation matrices customised for various data modalities and may also include modal information vectors. These parameters no longer rely on predefined encodings, but can be further trained by automatic learning algorithms.
2. Transformer-based optimisation of task model parameters.

After one round of global training, the participants upload their local parameters of each modal linear mapping matrix, modal embedding vector and Transformer task model to a central server for summary aggregation. The server applies the federated averaging method to compute the global modal linear mapping matrices, modal embedding vectors, and global parameters of the transformer model (Mu et al., 2022). Each participant trains the initial model parameters on local data, thus incorporating features and preferences into the model. Once the global model is trained, each participant can fine-tune the global model for their specific task requirements to obtain a local model. The personalised tuned local models are more accurately adapted to the local task than the global model.

The federated migration learning framework is given as an example with three participants A, B, and C, as shown in Figure 4, where each participant has data with different modalities, which are represented by different graphs (Δ, □, ○).

Figure 4 Federal transfer learning framework (see online version for colours)



Each participant uses its own data to generate local parameters in the local training model, which contains the linear mapping matrix of data modalities it has as well as the local task model parameters. These parameters obtained from training based on their respective data represent the knowledge learned independently from the local data by the local models of the three participants. After the aggregation process is completed, the central server obtains a global model parameter $\boldsymbol{P}$ and a global linear mapping matrix corresponding to each modality, which combine the local knowledge of all participants. The global model parameter $\boldsymbol{P}$ and the global linear mapping matrix $\boldsymbol{Q}_{\Delta/\square/\circ}$ for each modality are sent to each participant for updating the local model and the linear mapping matrices for different modalities of each participant, so that each model can obtain global knowledge from other participants and enhance the performance of the respective model. It is often required to find a balance between global consistency and local performance. After obtaining the global model, each participant can fine-tune the global model to obtain a personalised multimodal model that is better suited to its task based on its own modal data and specific task (Dong and Wang, 2023).

4.3 Steps for faulty line identification based on transformer-federation migration learning

The faulty line recognition process based on Transformer and federated migration learning is shown in Figure 5. Its specific realisation process is:

1 Voltages and currents at both ends of the DC line are collected at a frequency of 10 kHz for 10 ms before and 20 ms after the fault. Based on current and voltage signals, the fault sample matrix is formed as (14), and the dimension of each fault sample matrix is 300 × 68.

$$\begin{aligned} G = [&I_{1c}, U_{1c}, I_{1r}, U_{1r}, I_{2c}, U_{2c}, I_{2r}, U_{2r}, I_{3a}, U_{3a}, I_{3b}, U_{3b}, \\ &I_{3c}, U_{3c}, ..., I_{12a}, U_{12a}, I_{12b}, U_{12b}, I_{12c}, U_{12c}] \end{aligned} \tag{14}$$

where I_{1c}, U_{1c} and I_{2c}, U_{2c} for DC line $L1$ and $L2$, respectively, the sender current, voltage. I_{1r}, U_{1r} and I_{2r}, U_{2r}, respectively, for DC line $L1$ and $L2$, the receiving end of the current, voltage. I_{3a}, U_{3a}, I_{3b}, $\cdots$, U_{12b}, I_{12c}, U_{12c}, respectively, for the AC line between the $L3$ and $L12$, the current and the voltage.

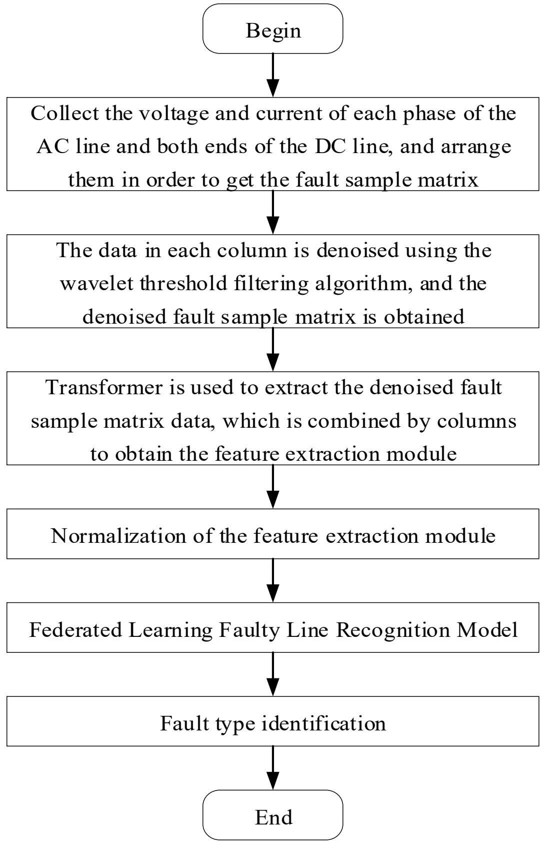
2 Use the wavelet threshold filtering algorithm to denoise the data in each column to obtain the denoised fault sample matrix.

3 The transformer is used to extract each column of the denoised fault matrix to obtain a 1×68 feature extraction module for each fault sample matrix.

4 Max-Min normalise each feature extraction module and input it into the federated migration learning fault line identification model for fault line identification.

5 Output the classification results.

Figure 5 Transformer-federation migration learning process for faulty line identification



5 Experimental results and analysis

The simulation experiments are run on a high-performance computer, in which the simulation experiments are run on a hardware operating environment of CPU Core processor, GPU Intel Ruiju X, a software operating environment of Python language, and a deep learning framework of Pytorch, and the detailed parameters are shown in Table 2. (Qudaih et al., 2013)

Table 2 Experimental parameters for failure risk assessment

Item	*Parameter*
CPU	Intel Core i7-1360P
GPU	Intel Ruiju X
System	Windows 10
Development language	Python 3.9
Deep learning framework	Pytorch 2.0
Development tool	Pycharm-2024

5.1 Experimental parameter design

Considering that the faults occurring in AC-DC hybrid grid lines are mainly single-pole ground faults, therefore, for two DC lines with a length of 500 km, five fault distances of single-pole ground fault simulation are set up in this paper, which are 100, 200, 250, 300, and 400, respectively, and the simulation is carried out for 10 transition resistances of 0.1, 0.5, 1, 2, 5, 10, 20, 50, 100, and 200Ω for each kind of fault distance. Ω for a total of 10 transition resistances are simulated for a total of 100 sets of DC side fault samples. For the 10 AC lines, a total of 10 fault types are considered. A total of 10 transition resistor cases under each fault distance are simulated, totalling 1,000 groups of fault samples on the AC side. A total of 1,100 groups of fault samples are obtained from 12 lines to form the dataset, as shown in Table 3.

Table 3 Fault sample dataset

	Fault line	*Sample size*
DC line	DC line L1 fault	50
	DC line L2 fault	50
AC line	AC line L3 fault	100
	AC line L4 fault	100
	AC line L5 fault	100
	AC line L6 fault	100
	AC line L7 fault	100
	AC line L8 fault	100
	AC line L9 fault	100
	AC line L10 fault	100
	AC line L11 fault	100
	AC line L12 fault	100

5.2 Model convergence analysis

The model is trained according to the designed framework and parameters, and the training loss and accuracy curves are given in Figures 6 and 7, respectively. Within the initial ten global training rounds, a significant and rapid decrease in the training and validation loss metrics can be seen. This significant decrease demonstrates the accelerated adaptation of the model to the complexity of the training dataset. After the 20th global training communication round, the curve describing the loss is found to flatten out, which indicates that the model has matured in terms of learning and is approaching its optimal performance state, and the performance of the multimodal global model begins to converge.

The waveforms before and after adding 10 dB noise filtering to the A-phase voltage signal collected under the fault of L12 are given in Figure 8. After the filtering process, the 10 dB noise signal is more similar to the pure signal waveform. The parameter is 0.99737, which shows that the filtering algorithm has a strong filtering ability for noise-containing signals, and at the same time, it can effectively retain the fault information and reduce the interference of noise on the fault signal.

Figure 6 Training process loss values (see online version for colours)

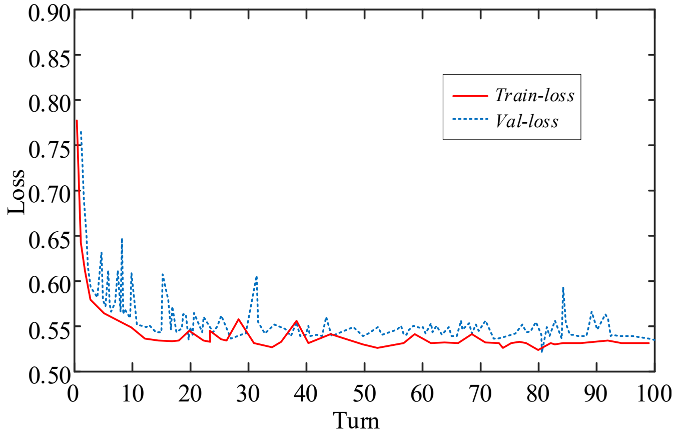
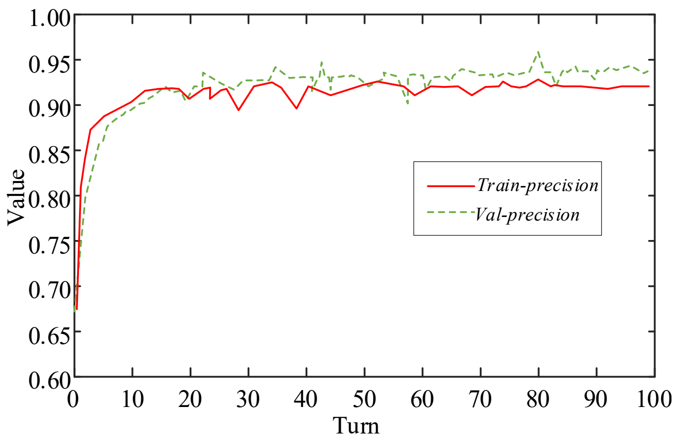


Figure 7 Precision values during training (see online version for colours)



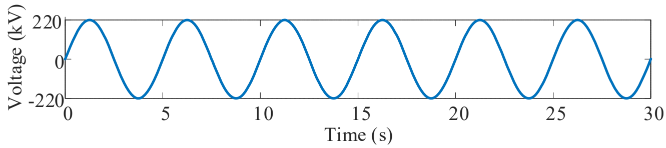
5.3 Fault analysis under different models

The FMEA and FTA methods are classical mathematical model theories for faults. Taking L2 line faults as the simulation scenario for power grid operation, this paper uses FMEA and FTA methods for fault diagnosis and analysis. The identification of L2 faults in AC/DC power grids using different methods is shown in Table 4.

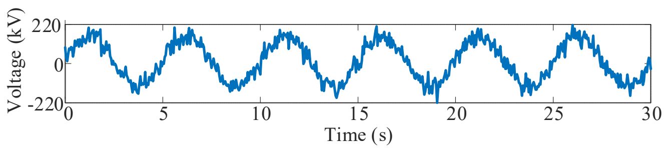
Table 4 Diagnosis of L2 line faults

Method	*Convergence time (s)*	*Recognition accuracy (%)*
FMEA	11.09	97.25
FTA	9.83	96.25
Transformer-federation migration learning model	5.25	99.10

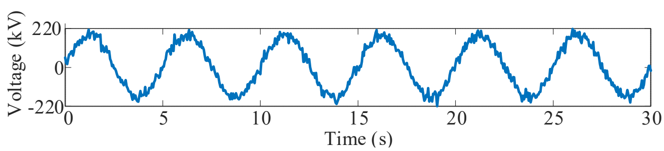
Figure 8 Voltage signals collected under a fault in L12, (a) original signal (b) original signal (with noise) (c) post-processed signals (see online version for colours)



(a)



(b)



(c)

As shown in Table 4, all experimental methods can achieve relatively accurate diagnosis of L2 line faults, but there are significant differences in identification time. The reason for this phenomenon is that the essence of FMEA and FTA methods is to adjust model parameters to achieve model optimisation design. For complex AC/DC systems, FMEA and FTA methods require precise parameter tuning of the grid operation in the early stage of diagnostic analysis. However, the deep learning model proposed in this paper can quickly and adaptively adjust based on the operation of the power grid, achieving fast state estimation and fault diagnosis.

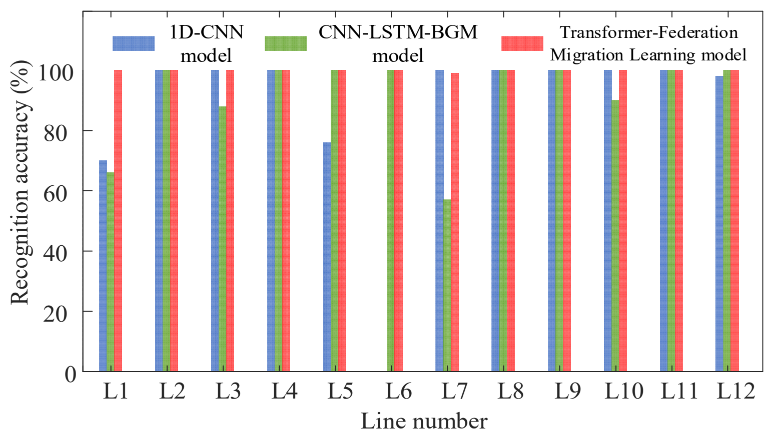
To demonstrate the excellence of the performance of the transformer-federated migration learning fault assessment model, this paper uses (Alhanaf et al., 2023) and (Gokulraj and Venkatramanan, 2024) as comparative methods for simulation verification. All the fault assessment methods are run in the same environment. In Alhanaf et al. (2023), 1D-CNN method is used to realise the grid operation state detection. In Gokulraj and Venkatramanan (2024), fault detection is realised for microgrid based on CNN-LSTM-GBM network model.

The 1D-CNN model and CNN-LSTM-GBM network model are tested for fault line identification. The convergence performance and recognition accuracy using different fault assessment models are compared in Table 5. The proposed transformer-federation migration learning-based fault assessment model converges faster, and can realise the effective calculation and analysis of AC-DC hybrid grid fault data within 7.28 s, with an accuracy rate of up to and 0.95 s shorter than the analysis and calculation time of the 1D-CNN method. Meanwhile, the data analysis time of the CNN-LSTM-GBM method in (Gokulraj and Venkatramanan, 2024) is 7.92 s, although the performance of the transformer-federation migration learning model is similar to that of the transformer-federation migration learning model in terms of time, the accuracy rate of the CNN-LSTM-GBM method in identifying faults is 92.2%, which is not able to realise the high-precision identification of the actual engineering. Therefore, the transformer-federation migration learning model proposed in this paper not only improves the fault line recognition accuracy, but also improves the convergence speed with higher accuracy and stability.

Table 5 Convergence performance and recognition accuracy of different models

Method	*Convergence time (s)*	*Recognition accuracy (%)*
1D-CNN model	8.51	92.7
CNN-LSTM-GBM model	9.82	92.2
Transformer-federation migration learning model	7.28	99.5

Figure 9 Recognition rate of different models for each fault line (see online version for colours)



The recognition accuracies of different models for different fault lines are shown in Figure 9, which shows that the CNN-LSTM-GBM model is difficult to learn effective information when dealing with the AC-DC hybrid grid fault feature module, resulting in a lower recognition accuracy. Especially, it is unable to make effective judgment when dealing with symmetrical line fault information, and the 1D-CNN model and CNN-LSTM-GBM model have poor recognition accuracy for lines L6 and L12, while the 1D-CNN model and CNN-LSTM-GBM model are unable to recognise lines L9 and L6.

According to Table 4 and Figure 9, it can be seen that the Transformer-federation migration learning model has advantages such as fast convergence and recognition speed, high recognition accuracy, and full-channel recognition. This indicates that the application of this model can basically identify faults in the initial stage of link faults and make strategic adjustments as soon as possible to improve the power supply reliability of the AC/DC hybrid power grid. Therefore, faults can be curbed in the initial stage, preventing link faults from spreading and causing more serious harm.

6 Conclusions

This paper proposes a chain fault risk assessment method based on the transformer-federation migration learning mechanism for AC-DC hybrid grids, and verifies the validity and reasonableness of the proposed assessment method by combining theoretical modelling, simulation analysis, and performance comparison, with the main conclusions as follows:

1 The chain fault risk assessment method based on transformer-federation migration learning mechanism can quickly assess the chain fault risk of AC-DC hybrid grids and accurately recognise the chain fault sequences with higher risk based on different initial faults, and compared with the traditional method, the convergence speed of this paper's method for chain fault risk assessment can be shortened by 2.54 s, and the fault recognition accuracy is up to 99%. The accuracy rate is as high as 99.5%.

2 Compared with other traditional methods, the chained fault risk assessment method based on the Transformer-Federation migration learning mechanism is more effective in the identification of faulted lines in AC-DC hybrid grids, and it can cover all AC-DC faulted lines.

In future research, we will consider the scenario where multiple lines and multiple types of lines fail simultaneously, expand the number of fault samples, and improve the generalisation ability and practicality of the proposed method. We will conduct in-depth exploration on the collaborative optimisation method of control and protection for inhibiting the spread of cascading faults, comprehensively verify the applicability of the proposed risk assessment method in AC/DC hybrid grids, and lay a solid theoretical foundation for further promoting its application. In addition, we will integrate and explore operational data and develop tools for automatically identifying link faults. Furthermore, we will expand the research process to form a dynamic safety assessment system.

Declarations

All authors declare that they have no conflicts of interest.

Data availability statement

The datasets used and analysed during the current study available from the corresponding author on reasonable request.

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