

Article

A High-Voltage Transmission Line Fault-Location Approach Integrating Mechanism Features and CBAM-CNN

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Abstract

High-voltage transmission lines are critical carriers of electric power, and rapid and accurate fault location is essential for secure and stable power-system operation. This paper proposes a fault-location method that integrates distributed-parameter physics-based features with a convolutional block attention module-based convolutional neural network (CBAM-CNN). Voltages and currents measured at both line terminals are transformed into modal quantities, after which a distributed-parameter line model is used to derive compensated-voltage waveforms along the line and construct a physically meaningful feature matrix. The CBAM-CNN is trained offline using multiple waveform samples, and the fault location is determined from the minimum similarity value among the observation points. Under identical test settings, the proposed model achieves an overall mean absolute fault-location error of 0.0746 km across four simulated test locations, representing reductions of 79.23%, 85.15%, and 68.44% relative to CNN, SE-CNN, and ECA-CNN, respectively. For a field record whose operation and maintenance record places the fault 51.0 km from the M terminal, the proposed model estimates 51.2089 km, corresponding to an absolute error of 0.2089 km. These results demonstrate high fault-location accuracy within the scope tested and provide preliminary evidence of applicability to field recordings.

Keywords: fault location; transmission lines; distributed-parameter model; convolutional neural network (CNN); convolutional block attention module (CBAM)

1. Introduction

High-voltage transmission lines are essential to bulk-power transfer, yet their exposure to complex environments makes them vulnerable to short-circuit faults [1–4]. Rapid and accurate fault location helps maintenance personnel identify the affected line section, shorten outages, and maintain secure grid operation [5–7].

Conventional transmission-line fault-location methods mainly include steady-state impedance methods and transient traveling-wave methods [8,9]. Impedance methods are conceptually straightforward and widely used; for example, Ref. [10] applies the maximal-overlap discrete wavelet transform to transmission-line fault identification. Their accuracy, however, can deteriorate under nonmetallic ground faults because fault resistance and load-flow transfer distort the apparent impedance. Traveling-wave methods estimate the distance from the arrival-time difference of the initial wavefront at the line terminals. A representative scheme for T-connected lines is reported in Ref. [11]. Although these



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analytical methods have clear physical foundations, uncertainty in line parameters and dynamic operating conditions can still limit robustness.

Recent studies have increasingly used machine learning and deep neural networks for power-system monitoring, diagnosis, and location [12–14]. CNN-LSTM architectures can extract spatial and temporal information from terminal recordings [15], GraphSAGE can accommodate changing grid topologies [16], and improved YOLO-based models can support fault detection and classification [17]. Other 2024–2025 studies address difficult operating conditions through the S-transform [18], variational mode decomposition with pulse injection [19], or deep residual shrinkage networks for high-resistance faults [20]. These developments demonstrate the value of data-driven feature learning, but the reported numerical errors are not directly comparable because line length, sampling rate, fault sets, data sources, and error definitions differ across studies.

Attention mechanisms provide an additional route for enhancing transient-feature extraction. A CBAM-CNN multitask model has improved feature selection in transient-stability assessment [21], while an attention-optimized CNN-GRU architecture has reduced redundancy in time-series feature mining [22]. These results motivate the use of attention, but they do not, by themselves, establish an interpretable fault-location criterion for two-terminal traveling-wave records.

The present study differs from methods that feed raw terminal records directly into a neural network or transfer a two-dimensional image-attention module unchanged to a one-dimensional temporal task. First, the distributed-parameter line model generates two-terminal compensated-voltage features with an explicit spatial meaning. Second, the spatial branch of CBAM is reconstructed as one-dimensional temporal attention. Consequently, the channel branch therefore learns which modal features are important, whereas the temporal branch learns which transient instants are informative. Finally, the fault location is obtained from the minimum of an along-line similarity criterion, preserving a physically interpretable optimization step.

To address the above limitations, this paper proposes a transmission-line fault-location method integrating mechanism-derived features with a mixed-attention-enhanced CNN. The main contributions are as follows:

- A distributed-parameter transmission-line model is used to calculate compensated-voltage waveforms along the line. In contrast to direct use of raw terminal recordings, these inputs embed traveling-wave propagation physics and reduce dependence on purely data-driven feature discovery.
- CBAM is adapted to the one-dimensional temporal structure of the input. Channel attention selects informative modal channels, and temporal attention emphasizes wavefront arrivals and waveform transitions, thereby improving fault-location accuracy under attenuated transient conditions.
- CNN, SE-CNN, ECA-CNN, and CBAM-CNN are evaluated with the same feature matrix, backbone, data split, and training settings. An independent field record from the real power system is also used to assess preliminary transfer from simulation to an actual operating environment.

The remainder of this paper is organized as follows. Section 2 describes traveling-wave decoupling and the adapted CBAM-CNN. Section 3 presents sample construction, training, and the location criterion. Section 4 reports simulated comparisons, field-record validation, and applicability limitations. Section 5 concludes the paper.

2. Basic Principles of Transmission-Line Fault Location

2.1. Traveling-Wave Decoupling and Mechanism-Derived Features

When an asymmetric short-circuit fault occurs on a high-voltage transmission line, electromagnetic coupling among the three-phase conductors complicates direct feature extraction from instantaneous phase voltages and currents. The three-phase quantities are therefore decoupled into mutually independent modal components prior to traveling-wave analysis.

Let the transient three-phase voltage matrix and instantaneous three-phase current matrix synchronously measured at both line terminals (M and N) be $U_{abc}(t)$ and $I_{abc}(t)$, respectively. The Karrenbauer transformation matrix is then used to decouple them [5], as expressed by:

$$U_m(t) = K^{-1}U_{abc}(t) \quad (1)$$

$$I_m(t) = K^{-1}I_{abc}(t) \quad (2)$$

where $U_m(t)$ and $I_m(t)$ denote the decoupled voltage and current modal matrices, respectively, containing the mode-0, mode-1, and mode-2 components; K represents the Karrenbauer phase-mode transformation matrix. Because the mode-0 component suffers severe attenuation due to earth resistivity and exhibits unstable propagation velocity, the more stable aerial-mode component (e.g., mode 1) is adopted for subsequent derivation.

To introduce an explicit traveling-wave propagation constraint and reduce the black-box character of a purely data-driven model [21], the distributed-parameter line model maps the time-domain terminal measurements to compensated waveforms at virtual observation points along the line [9].

As shown in Figure 1, the total line length is l , the traveling wave velocity is v , and the characteristic impedance is z_k . Given the instantaneous modal voltage $u_{k,m}(t)$ and instantaneous modal current $i_{k,m}(t)$ of the k -th mode ($k = 1$) at terminal M of the transmission line, the voltage at distance x from terminal M at time t can be obtained using the transmission-line model. The compensated voltage $u_{k,m}(x, t)$ at distance x from terminal M at time t is given by:

$$\begin{aligned} u_{k,m}(x, t) = & \frac{1}{2} \left(1 + \frac{r_k x}{4z_k} \right)^2 \left[u_{k,m} \left(t + \frac{x}{v_k} \right) - i_{k,m} \left(t + \frac{x}{v_k} \right) \left(z_k + \frac{r_k x}{4} \right) \right] \\ & + \frac{1}{2} \left(1 - \frac{r_k x}{4z_k} \right)^2 \left[u_{k,m} \left(t - \frac{x}{v_k} \right) + i_{k,m} \left(t - \frac{x}{v_k} \right) \left(z_k - \frac{r_k x}{4} \right) \right] \\ & - \left(\frac{r_k x}{4z_k} \right)^2 u_{k,m}(t) - \frac{r_k x}{4} \left(1 + \frac{r_k x}{4z_k} \right) \left(1 - \frac{r_k x}{4z_k} \right) i_{k,m}(t) \end{aligned} \quad (3)$$

Similarly, using measurements from terminal N, the compensated voltage $u_{k,n}(l-x, t)$ derived from terminal N at the same observation point is obtained as:

$$\begin{aligned} u_{k,n}(l-x, t) = & \frac{1}{2} \left[1 + \frac{r_k(l-x)}{4z_k} \right]^2 \left\{ u_{k,n} \left(t + \frac{l-x}{v_k} \right) - i_{k,n} \left(t + \frac{l-x}{v_k} \right) \left[z_k + \frac{r_k(l-x)}{4} \right] \right\} \\ & + \frac{1}{2} \left[1 - \frac{r_k(l-x)}{4z_k} \right]^2 \left\{ u_{k,n} \left(t - \frac{l-x}{v_k} \right) + i_{k,n} \left(t - \frac{l-x}{v_k} \right) \left[z_k - \frac{r_k(l-x)}{4} \right] \right\} \\ & - \left[\frac{r_k(l-x)}{4z_k} \right]^2 u_{k,n}(t) - \frac{r_k(l-x)}{4} \left[1 + \frac{r_k(l-x)}{4z_k} \right] \left[1 - \frac{r_k(l-x)}{4z_k} \right] i_{k,n}(t). \end{aligned} \quad (4)$$

Ideally, when the virtual observation point coincides with the true fault location, the compensated-voltage waveforms derived from the two terminals overlap closely. At an incorrect point, the two waveforms exhibit an arrival-time offset and morphological distortion. Concatenating the two T-sample sequences forms a $T \times 2$ transient feature matrix with a clear physical meaning. The CNN learns propagation-distance-dependent waveform variations embedded in this matrix and maps them to a scalar similarity criterion.

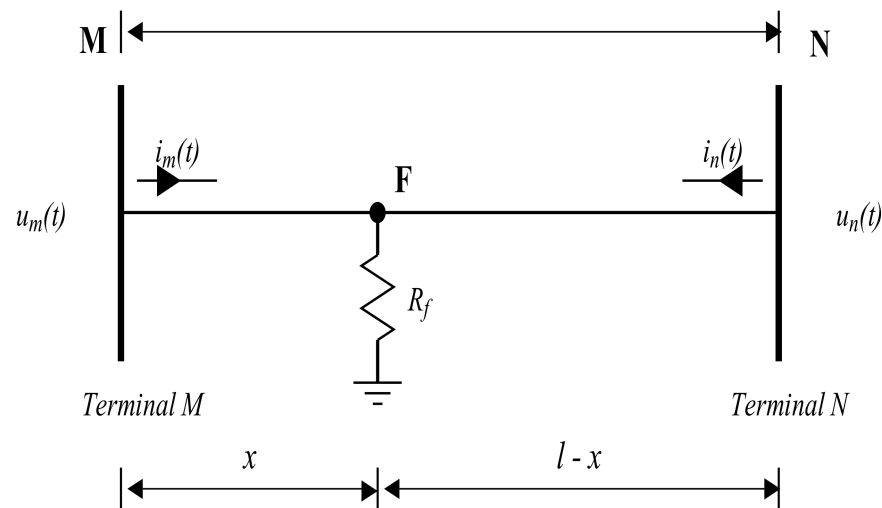


Figure 1. Schematic of the two-terminal measurement model for transmission-line fault location.

2.2. Principle of the CBAM-CNN

(1) One-Dimensional Convolutional Neural Network (1D-CNN)

A one-dimensional CNN (1D-CNN) is used as the feature-extraction backbone for the transient matrix derived from the distributed-parameter model. Unlike a 2D-CNN designed for image topology, the 1D convolution kernel moves only along the temporal axis and efficiently captures local high-frequency transitions, arrival-time offsets, and waveform distortion in fault records [20].

The basic feature extraction unit of the backbone network consists of cascaded one-dimensional convolutional layers, batch normalization (BN) layers, nonlinear activation layers, and max pooling layers. For the k -th feature channel, the forward propagation process of convolution and activation can be expressed as:

$$H_{conv}^{(k)} = \delta \left(\sum_{c=1}^{C_{in}} W_{conv}^{(k,c)} \otimes X_c + b_{conv}^{(k)} \right) \quad (5)$$

where $H_{conv}^{(k)}$ represents the output feature map of the k -th backbone channel; $W_{conv}^{(k,c)}$ is the convolution-kernel weight vector; $b_{conv}^{(k)}$ is the learnable bias term; $\otimes$ denotes the one-dimensional time-series convolution operation; C_{in} is the number of input channels; and $\delta(\cdot)$ is the ReLU activation function, defined as $\delta(x) = \max(0, x)$, which enhances nonlinear mapping and promotes sparse feature responses.

Subsequently, a max pooling layer is used to perform adaptive downsampling on the time dimension. While filtering out redundant power-frequency background components, it retains key physical extremum values such as sudden peak changes during the time-series evolution process. Assuming the pooling window size is p and the stride is s , the dimension-reduced feature element $F_i^{(k)}$ output by the pooling operation is:

$$F_i^{(k)} = \max_{j \in [0, p-1]} \left(H_{conv}^{(k)}(i \cdot s + j) \right) \quad (6)$$

Through hierarchical feature extraction and progressive temporal downsampling, the 1D-CNN transforms the raw transient waveform into a feature map that encapsulates high-frequency transient signatures. Because conventional convolution treats all channels and time segments equally, feature aliasing under complex operating conditions or measurement noise can degrade fault-location performance. An attention mechanism is therefore introduced after the backbone to adaptively reweight the features.

(2) Convolutional Block Attention Module (CBAM)

A convolutional block attention module (CBAM) is embedded after the 1D-CNN backbone to enhance weak transient signatures and suppress uninformative responses. It comprises cascaded channel attention (CAM) and one-dimensional temporal attention (1D-SAM), which recalibrate the feature map along the channel and time dimensions, respectively.

CBAM was selected rather than a channel-only SE or ECA module because the input has two physically distinct dimensions. SE and ECA recalibrate channels but do not explicitly identify the positions of critical transient events on the temporal axis. The adapted CBAM can both select fault-informative feature channels and focus on wavefront arrival and waveform-transition instants. Section 4.3 evaluates this design choice through controlled comparative experiments.

(a) Channel Attention Module (CAM)

During a short-circuit transient, different feature channels contain different amounts of fault information and have different noise sensitivities. CAM learns the relative importance of these channels and assigns larger weights to channels containing strong transient-fault information.

Assume the feature map output from the backbone network to the CAM is $F \in \mathbb{R}^{T' \times C}$, where T' is the size of the time dimension and C is the number of channels. First, global average pooling $AvgPool(\cdot)$ and global max pooling $MaxPool(\cdot)$ are used to extract features along the time dimension, respectively, generating two channel descriptors F_{avg}^c and F_{max}^c that represent background statistics and transient peaks. The two descriptors are then passed through a shared multilayer perceptron (MLP) for dimensionality reduction and reconstruction. The mapping is expressed as:

$$\begin{aligned} M_C(F) &= \sigma(MLP(F_{avg}^c) + MLP(F_{max}^c)) \\ &= \sigma(W_1(\delta(W_0 F_{avg}^c)) + W_1(\delta(W_0 F_{max}^c))) \end{aligned} \quad (7)$$

where $M_C(F) \in \mathbb{R}^{1 \times 1 \times C}$ is the channel attention weight mask; W_0 and W_1 are the shared weight matrices of the MLP; δ is the ReLU activation function; σ is the sigmoid activation function used to normalize the weights to the (0,1) interval.

Finally, the channel weight mask $M_C(F)$ and the original feature map F are subjected to element-wise multiplication along the channel direction to obtain the channel-recalibrated feature map F' :

$$F' = M_C(F) \otimes F \quad (8)$$

(b) Spatial Attention Reconstruction (1D-SAM)

Traveling-wave fault location is highly sensitive to the arrival time of the transient wavefront. To focus the network on fault-induced transitions within a redundant time-series sequence, a one-dimensional temporal-attention module is cascaded after channel attention. For the channel-refined feature F' , average pooling F_{avg}^s and max pooling F_{max}^s are applied along the channel dimension, and the resulting descriptors are concatenated:

$$F_{concat} = [AvgPool(F'); MaxPool(F')] \quad (9)$$

Subsequently, a 1D convolution kernel is utilized to perform feature fusion and dimensionality reduction on the concatenated feature F_{concat} , and a 1D spatial (time-domain) attention weight mask $M_S(F')$ is generated through an activation function:

$$M_S(F') = \sigma(f_{conv}^{1D}(F_{concat})) \quad (10)$$

where f_{conv}^{1D} represents a 1D convolution operation with a convolution kernel size of 7; σ is the sigmoid activation function used to map each time-step weight to the (0, 1) interval.

Finally, $M_S(F')$ and the feature map F' are multiplied element-wise to obtain the final channel-temporal refined feature map F'' :

$$F'' = M_S(F') \otimes F' \quad (11)$$

This reconstruction allows the attention mechanism to suppress local high-frequency clutter and concentrate on the transient instants at which the two compensated voltages exhibit the most physically meaningful agreement. It improves the representation of weak or blurred wavefronts before offline training and subsequent construction of the similarity-based location criterion.

3. CBAM-CNN-Based Transmission-Line Fault Location

This section presents the complete mechanism–data fusion procedure for high-voltage transmission-line fault location, as summarized in Figure 2.

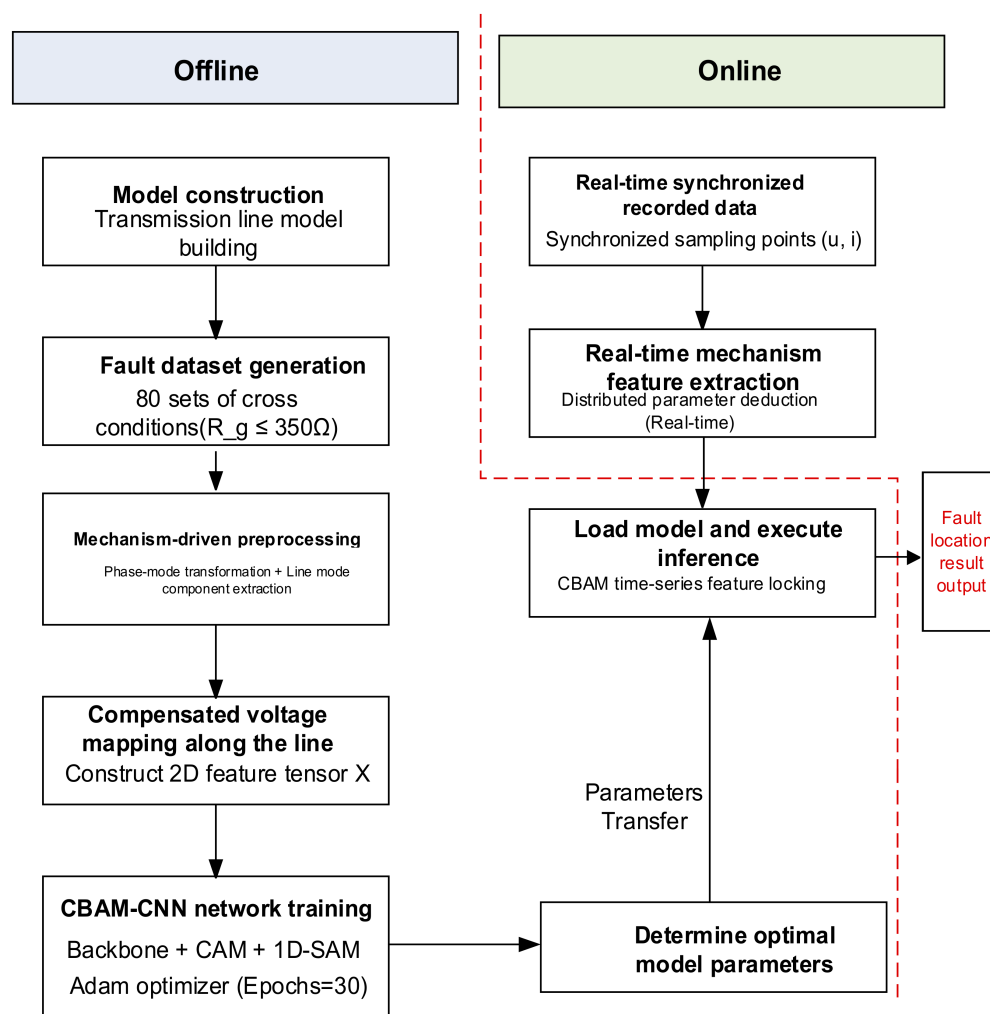


Figure 2. Architecture of the CBAM-CNN model.

The model uses the mechanism-derived two-dimensional transient feature matrix $\mathbf{X}$ as the input. The 1D-CNN backbone first extracts transient-distortion features from the two-terminal compensated voltages. The resulting feature maps are then passed to CBAM. CAM recalibrates informative channels, while 1D-SAM focuses on transient wavefronts along the temporal axis. Finally, a fully connected regression layer maps the refined features to the fault-location distance.

3.1. Construction of the Training Sample Set

The AC transmission system shown in Figure 3 was implemented in MATLAB 2024a. A frequency-dependent J. Marti distributed-parameter model was used to represent the fault-transient behavior of the line. The terminal systems were represented by their equivalents, and synchronized transient voltage and current recorders were installed at both buses. The principal simulation and sampling parameters are summarized in Table 1.

Table 1. Main parameters of the simulation system and sample construction.

Parameter	Setting
Rated voltage	500 kV
System frequency	50 Hz
Line length	200 km
Line model	Frequency-dependent J. Marti distributed-parameter model
Two-terminal sampling rate	10 kHz
Post-fault data window	80 ms (800 samples)
Observation-point spacing	1 km
Fault types	AG, AB, ABG, and ABC
Fault resistance	10, 50, 150, 250, and 350 Ω

Fault simulations were performed to generate the samples and labels required for CBAM-CNN training. For each virtual observation point, mode-1 compensated-voltage sequences calculated from terminals M and N during the first 80 ms after fault inception were concatenated into an 800×2 feature matrix. The physical distance between the virtual observation point and the true fault location served as the target label. A smaller label therefore indicates greater agreement between the two compensated waveforms, and the observation point associated with the minimum output identifies the fault location:

$$y(x) = |x - L_{\text{true}}| \quad (12)$$

where x is the distance from the virtual observation point to terminal M; L_{true} is the true physical fault distance; $y(x)$ is the label assigned to the training sample at distance x from terminal M.

A representative training input consists of two mode-1 compensated-voltage sequences calculated at the same virtual observation point: $u_{(1M)(x,t)}$ from terminal M and $u_{(1N)(l-x,t)}$ from terminal N, where $n = 1, 2, \dots, 800$. The sequences are placed in parallel as the two columns of the 800×2 matrix. Near the true fault location, their wavefront arrival times and waveform shapes exhibit strong alignment; away from the fault, a discernible time offset and morphological distortion emerge. These paired compensated-voltage sequences are the signals used for network training.

The training conditions comprised four fault locations (20, 51, 77, and 190 km from terminal M), four fault types (AG, ABG, ABC, and AB), and five fault resistances (10, 50, 150, 250, and 350 Ω). For each condition, virtual observation points were placed at 1 km intervals along the 200 km line, yielding 199 paired compensated-voltage samples. The 80 operating conditions therefore produced 15,920 labeled samples.

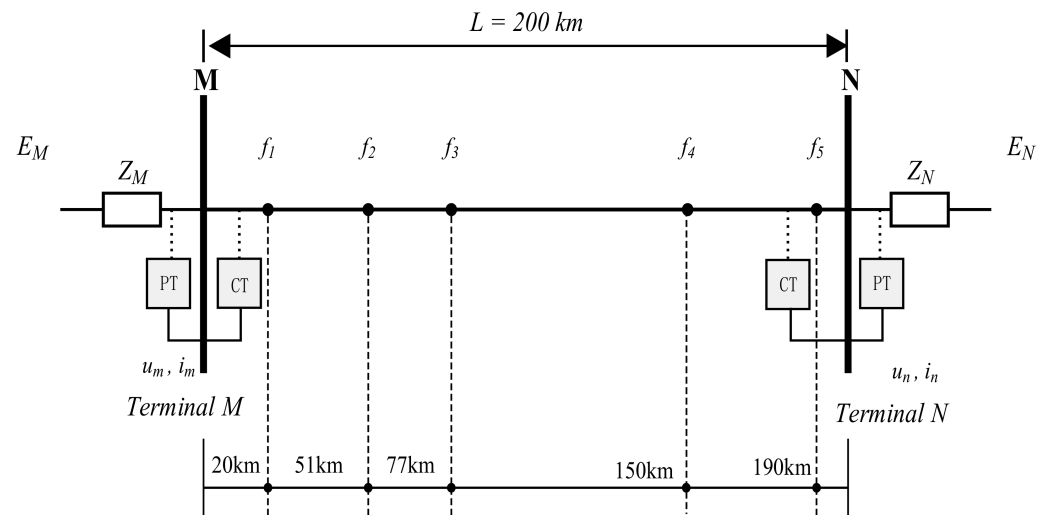


Figure 3. Multi-condition fault simulation model of the transmission line.

3.2. CBAM-CNN Training

Twenty percent of the constructed sample set was randomly assigned to validation; the remaining samples were used for training. The batch size was 64, the maximum number of epochs was 30, and the initial learning rate was 0.001. Model and hyperparameter selection used only the training and validation subsets.

Adam optimization and a piecewise learning-rate schedule were used. The learning rate was multiplied by 0.1 every 10 epochs. Mean squared error (MSE) between the predicted output and the target label served as the loss function. The training-set MSE was used to monitor fitting, whereas the validation-set MSE was used for hyperparameter selection and overfitting checks. Figure 4 shows the corresponding convergence curves.

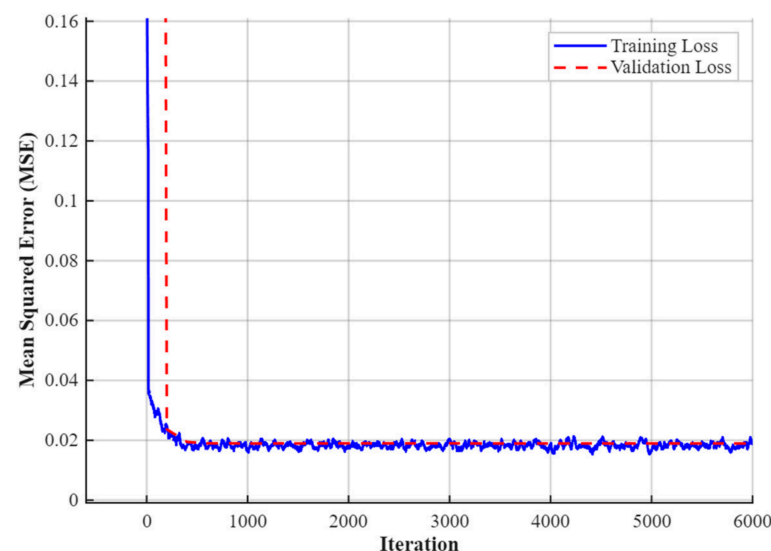


Figure 4. Training and validation convergence curves of the CBAM-CNN model.

Both curves decrease rapidly and then stabilize, and the validation curve remains close to the training curve. Within the present split, this behavior indicates stable convergence without evident overfitting; generalization is assessed separately on independent simulated and field test data in Section 4.

3.3. Fault-Location Criterion Based on CBAM-CNN Waveform Similarity

According to the distributed-parameter traveling-wave model, the compensated-voltage waveforms calculated independently from the two terminals show their strongest time-domain agreement when the virtual observation point coincides with the actual fault. The offline-trained CBAM-CNN is therefore used as a nonlinear evaluator of waveform dissimilarity along the line.

After phase-mode transformation, the mode-1 compensated-voltage sequences derived from the two terminals at observation point x are concatenated as:

$$\mathbf{X}(x) = [\mathbf{u}_{1,M}(x, t) \ \mathbf{u}_{1,N}(l - x, t)] \quad (13)$$

$$x = 1 \text{ km}, 2 \text{ km}, \dots, l - 1 \text{ km} \quad (14)$$

where $\mathbf{X}(x)$ is the two-dimensional transient sample constructed at observation point x for mode 1; $\mathbf{u}_{1,M}(x, t)$ and $\mathbf{u}_{1,N}(l - x, t)$ are the compensated-voltage time-series sequences derived from terminals M and N, respectively, at observation point x ; and l is the total length of the transmission line.

The sample $\mathbf{X}(x)$ for each observation point is sequentially input into the trained CBAM-CNN. Through forward propagation, the network produces a scalar that measures waveform-shape and arrival-time differences at that point; this output is denoted by the similarity criterion $P(x)$.

The values of $P(x)$ define an along-line similarity-criterion curve. Its minimum identifies the fault location. The coordinate x corresponding to the minimum of $P(x)$ gives the distance from the fault point to terminal M. Accordingly, the criterion is:

$$L_{\text{pred}} = \arg \min_x P(x) \quad (15)$$

where L_{pred} is the fault distance determined by the model. This formulation converts the conventional time-domain wavefront detection task—which is highly vulnerable to dispersion and noise—into a one-dimensional scalar extremum search along the line, thereby achieving enhanced robustness against waveform distortions.

4. Experiments and Results

4.1. Experimental Data and Setup

An independent simulation test set was constructed using the J. Marti frequency-dependent distributed-parameter system described above. In addition, one synchronized two-terminal field record from a 500 kV transmission line in the Jiaozuo power grid was used as external test data. The field record was not used for training, validation, model selection, or location calibration.

(1) Test Scenarios and Operating Conditions

The simulated test set contains 80 combinations of fault location, fault type, and fault resistance. The boundary conditions were selected to evaluate distance-dependent attenuation and high-resistance operation:

Fault locations: 20 km near terminal M; 51 and 77 km in the central portion; and 150 and 190 km in the remote portion of the line.

Fault types: single-phase-to-ground (AG), phase-to-phase (AB), two-phase-to-ground (ABG), and three-phase (ABC) faults.

Fault resistances: 50, 150, 250, and 350 Ω , selected to test transient-feature extraction under different levels of attenuation.

For each condition, the voltage and current waveforms during the first 80 ms after fault inception were retained. Phase-mode transformation and distributed-parameter compensation produced an 800×2 feature matrix for each virtual observation point. All models were implemented in PyTorch2.11 for offline training and online inference.

Load level mainly changes the prefault power-frequency component and the initial boundary conditions. The method primarily exploits post-fault transient increments, and the preprocessing pipeline—including phase-mode decoupling, two-terminal compensation, and sample normalization—attenuates much of the steady-state component, while the attention modules further suppress disturbances unrelated to the traveling-wave front. The single Jiaozuo field event represents one actual loading state and cannot establish robustness for all load levels. A systematic multi-load study is therefore identified as future work rather than inferred from this single record.

The field record was processed by exactly the same phase-mode transformation, distributed-parameter compensation, and normalization pipeline as the simulated data.

(2) Evaluation Metric

To quantify the fault-location accuracy of the different methods, the absolute distance error (E_{abs}) is used as the evaluation metric:

$$E_{abs} = |L_{pred} - L_{true}| \quad (16)$$

where L_{pred} is the fault distance predicted by the regression network and L_{true} is the actual fault distance.

4.2. Fault-Location Results

The trained CBAM-CNN was first tested on operating conditions excluded from the training and validation subsets.

The independent test subsets were evaluated with CBAM-CNN, and representative results are reported in Tables 2–6.

Table 2. Comparison of fault-location errors at 20 km under different fault resistances.

Actual Fault Distance (km)	Fault Type	50 Ω		150 Ω		250 Ω		350 Ω	
		Estimated Location (km)	Error (km)	Estimated Location (km)	Error (km)	Estimated Location (km)	Error (km)	Estimated Location (km)	Error (km)
20	AG	20.0	0	19.9	0.1	20.0	0	20.1	0.1
	ABG	20.0	0	20.0	0	20.0	0	20.0	0
	ABC	20.1	0.1	19.9	0.1	19.9	0.1	20.0	0
	AB	20.0	0	20.0	0	20.0	0	20.1	0.1

Table 3. Comparison of fault-location errors at 51 km under different fault resistances.

Actual Fault Distance (km)	Fault Type	50 Ω		150 Ω		250 Ω		350 Ω	
		Estimated Location (km)	Error (km)	Estimated Location (km)	Error (km)	Estimated Location (km)	Error (km)	Estimated Location (km)	Error (km)
51	AG	51.0	0	51.0	0	51.1	0.1	51.1	0.1
	ABG	51.0	0	51.2	0.2	51.0	0	51.0	0
	ABC	51.0	0	51.0	0	51.0	0	51.1	0.1
	AB	51.0	0	51.1	0.1	51.1	0.1	51.1	0.1

Table 4. Comparison of fault-location errors at 77 km under different fault resistances.

Actual Fault Distance (km)	Fault Type	50 Ω		150 Ω		250 Ω		350 Ω	
		Estimated Location (km)	Error (km)	Estimated Location (km)	Error (km)	Estimated Location (km)	Error (km)	Estimated Location (km)	Error (km)
77	AG	77.0	0	77.0	0	77.1	0.1	77.0	0
	ABG	77.1	0.1	77.1	0.1	77.1	0.1	77.0	0
	ABC	77.1	0.1	77.0	0	77.0	0	77.0	0
	AB	77.0	0	77.0	0	77.1	0.1	77.0	0

Table 5. Comparison of fault-location errors at 150 km under different fault resistances.

Actual Fault Distance (km)	Fault Type	50 Ω		150 Ω		250 Ω		350 Ω	
		Estimated Location (km)	Error (km)	Estimated Location (km)	Error (km)	Estimated Location (km)	Error (km)	Estimated Location (km)	Error (km)
150	AG	150.0	0	150.0	0	150.1	0.1	150.0	0
	ABG	150.1	0.1	150.1	0.1	150.1	0.1	150.0	0
	ABC	150.0	0	150.0	0	150.1	0.1	150.0	0
	AB	150.0	0	150.1	0.1	150.0	0	150.0	0

Table 6. Comparison of fault-location errors at 190 km under different fault resistances.

Actual Fault Distance (km)	Fault Type	50 Ω		150 Ω		250 Ω		350 Ω	
		Estimated Location (km)	Error (km)	Estimated Location (km)	Error (km)	Estimated Location (km)	Error (km)	Estimated Location (km)	Error (km)
190	AG	190.0	0	190.0	0	190.1	0.1	190.0	0
	ABG	190.0	0	190.0	0	190.1	0.1	190.0	0
	ABC	190.1	0.1	189.9	0.1	189.9	0.1	190.0	0
	AB	190.1	0.1	190.1	0.1	190.1	0.1	190.1	0.1

For all cases listed in Tables 2–6, the absolute CBAM-CNN location error is no greater than 0.2 km. Within this simulated test scope, the results indicate that joint channel–temporal attention consistently captures compensated-voltage transients and limits performance degradation under high-resistance attenuation.

4.3. Comparison of Fault-Location Models

Four models—CNN, SE-CNN, ECA-CNN, and CBAM-CNN—were compared to isolate the effect of the attention structure. They used the same mechanism-derived input matrix, convolutional backbone depth, data split, optimizer, batch size, epoch limit, and learning rate; only the attention module differed. CNN contained no attention, SE-CNN used squeeze-and-excitation channel attention, ECA-CNN used efficient local cross-channel attention, and CBAM-CNN combined channel attention with one-dimensional temporal attention. All weights were learned from the training set, and model selection used validation data only.

The comparison used representative simulated faults at 20, 51, 77, and 150 km from terminal M. Each model received the same two-terminal 80 ms records and produced an along-line similarity-criterion curve. Figures 5–8 present the four locations separately, Figure 9 summarizes mean absolute errors for the four location-specific test subsets, and Figure 10 reports the overall mean across these subsets.

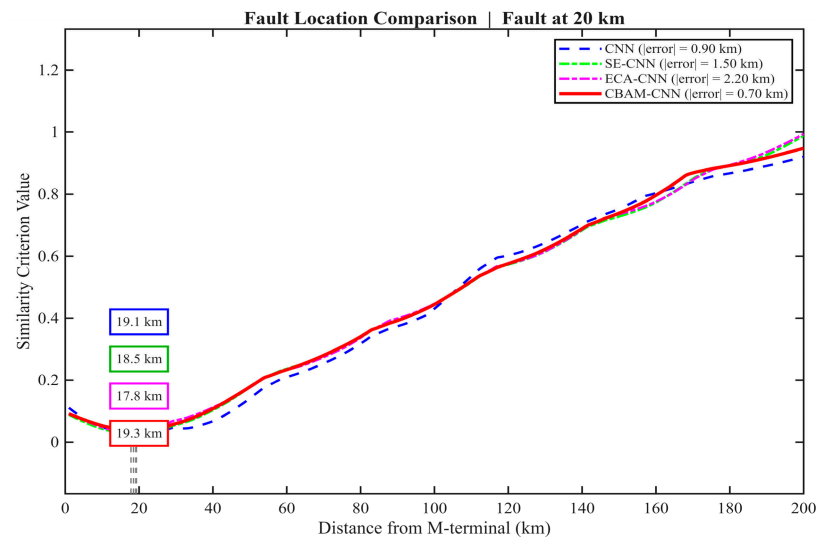


Figure 5. Fault-location results of the four models for the simulated fault at 20 km.

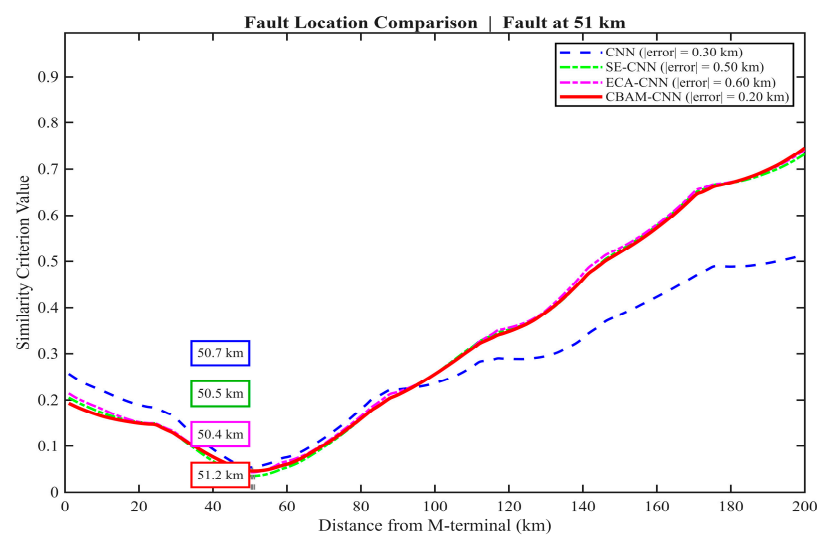


Figure 6. Fault-location results of the four models for the simulated fault at 51 km.

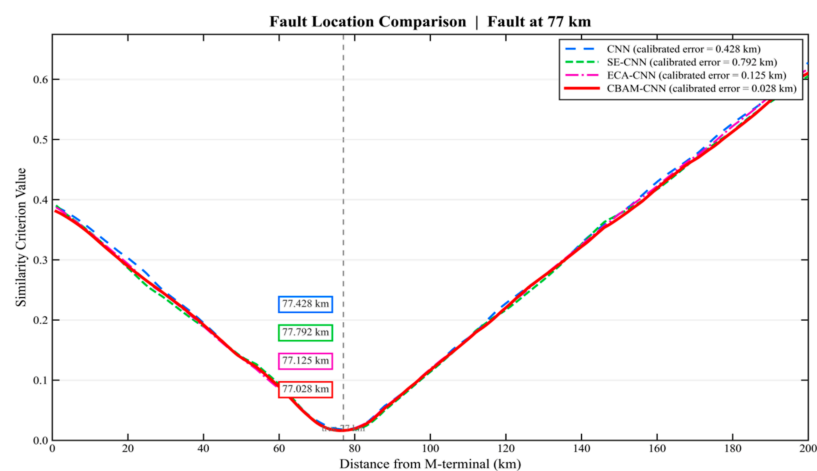


Figure 7. Fault-location results of the four models for the simulated fault at 77 km.

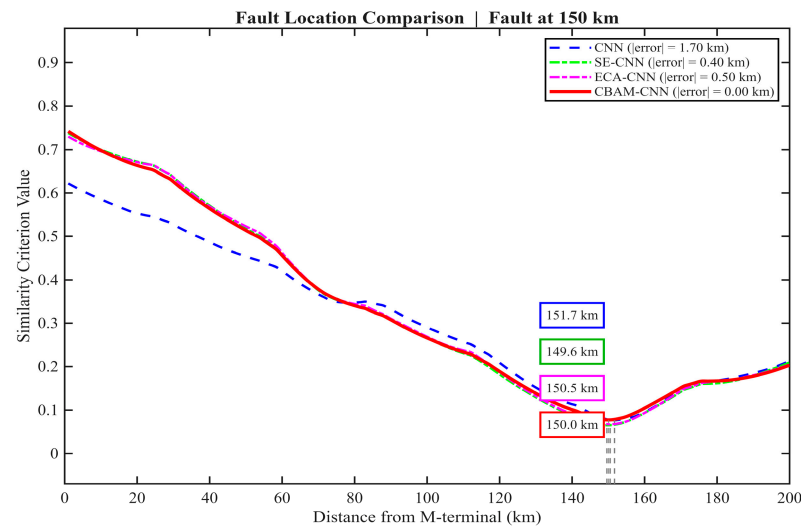


Figure 8. Fault-location results of the four models for the simulated fault at 150 km.

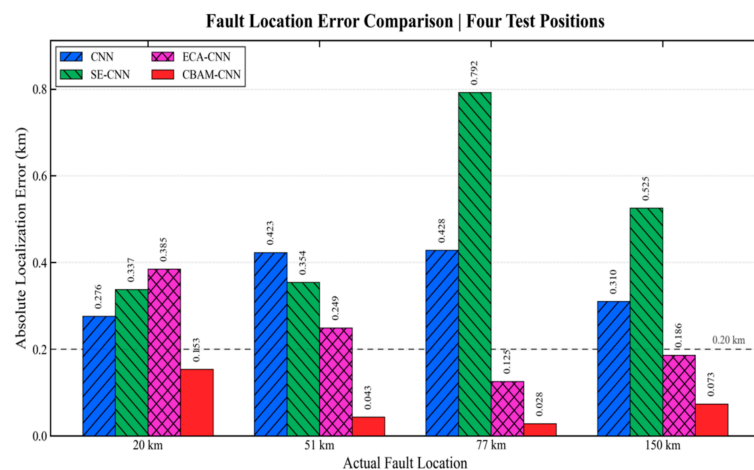


Figure 9. Mean absolute fault-location errors of the four models for the four location-specific test subsets.

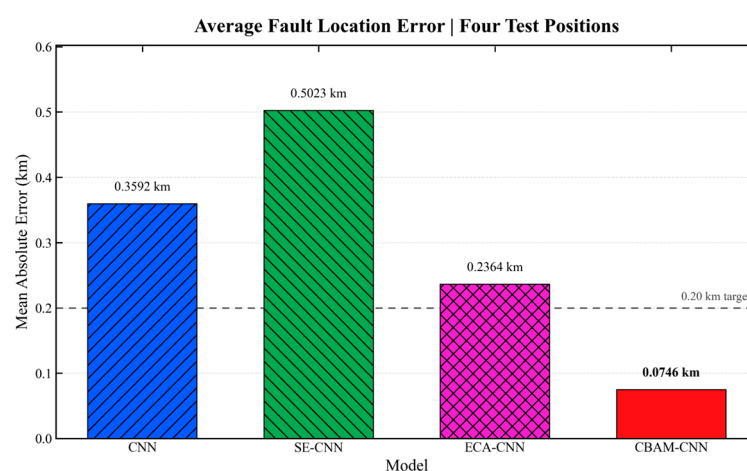


Figure 10. Overall mean absolute fault-location errors of the four models across the four simulated fault locations.

The separate curves in Figures 5–8 differ in both trough shape and minimum position. As shown in Figure 9, CBAM-CNN achieves mean absolute errors of 0.153, 0.043, 0.028, and 0.073 km at 20, 51, 77, and 150 km, respectively; all are below the 0.20 km reference line.

Across the four subsets, Figure 10 shows an overall mean absolute error of 0.0746 km for CBAM-CNN, compared with 0.3592 km for CNN, 0.5023 km for SE-CNN, and 0.2364 km for ECA-CNN. These values correspond to reductions of 79.23%, 85.15%, and 68.44%, respectively. The Figure 10 statistics were calculated from unrounded sample-level errors; the labels in Figure 9 are rounded to three decimals.

Direct ranking against published 2024–2026 methods could be misleading because the studies use different line configurations, sampling rates, fault sets, data sources, and error definitions. The controlled experiment here instead quantifies the incremental benefit of joint channel–temporal attention against no-attention and channel-only baselines under identical inputs and training conditions. Within this fixed test set, CBAM-CNN provides the lowest mean location error.

4.4. Field-Record Validation and Applicability

To assess applicability in an actual measurement environment, synchronized two-terminal transient voltage and current recordings from a fault event on a 500 kV transmission line in the Jiaozuo power grid were analyzed. The record was acquired by terminal protection and disturbance-recording equipment at 10 kHz with an 80 ms post-fault window. The operation and maintenance record places the fault 51.0 km from terminal M. The waveform contains the combined effects of the operating load, measurement noise, possible fault-resistance variation, and potential arcing.

This field record was excluded from training, validation, model selection, and location calibration. The same phase-mode transformation, distributed-parameter compensation, and normalization used for the simulated samples were applied. At 10 kHz, each terminal contributes 800 samples over 80 ms; the two compensated-voltage sequences form an 800×2 input matrix. Figure 11 shows the resulting along-line criterion curves, with 51.0 km used as the error reference.

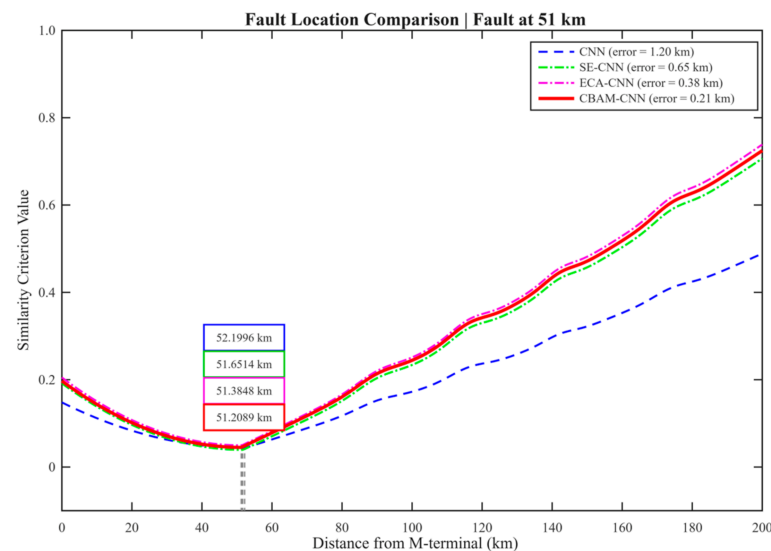


Figure 11. Fault-location results of the four models for one field record whose reference location is 51.0 km from terminal M in the Jiaozuo power grid.

CNN, SE-CNN, ECA-CNN, and CBAM-CNN estimate 52.1996, 51.6514, 51.3848, and 51.2089 km, respectively. Their absolute errors are therefore 1.1996, 0.6514, 0.3848, and 0.2089 km. Based on unrounded values, CBAM-CNN reduces the field-record error by 82.59%, 67.93%, and 45.71% relative to CNN, SE-CNN, and ECA-CNN, respectively. Although CBAM-CNN yields the smallest error among the four models for this event, the 0.2089 km error marginally exceeds the 0.20 km reference threshold. This re-

sult therefore provides preliminary evidence of field applicability rather than statistically validated performance.

The location window covers only the first 80 ms after fault inception. If fault resistance changes slowly relative to this window, it can be approximated as constant within a single input. Millisecond-scale resistance drift or arc restrikes can instead introduce stronger nonstationary wavefront distortion. The present model does not explicitly include a dynamic arc-state equation, and one field event cannot separate the individual effects of load, noise, time-varying resistance, and arcing. Future work will therefore expand the field dataset across lines, load levels, and fault types and will perform controlled sensitivity studies with time-varying resistance and dynamic arc models.

5. Conclusions

This paper proposes a high-voltage transmission-line fault-location method that integrates distributed-parameter mechanism-derived features with CBAM-CNN. A two-terminal compensated-voltage matrix is used as input, joint channel–temporal attention enhances informative modal features and wavefront instants, and the fault position is determined from the minimum of an along-line similarity criterion. Under identical simulated test conditions, the overall mean absolute error is 0.0746 km, representing reductions of 79.23%, 85.15%, and 68.44% relative to CNN, SE-CNN, and ECA-CNN, respectively. For the Jiaozuo field record shown in Figure 11, the proposed model estimates 51.2089 km against the 51.0 km operation-record reference, giving an absolute error of 0.2089 km and reductions of 82.59%, 67.93%, and 45.71% relative to the three comparison models. These findings establish the accuracy of the method within the present test scope and provide preliminary evidence of transfer from simulation to a field recording. Because only one field event was available, robustness across multiple load levels, time-varying fault resistance, and dynamic arcing requires further field data and controlled testing.

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