

A Hybrid Deep-Learning and Impedance-Based Scheme for Fault Classification and Location in Transmission Lines: A Physics-Validated, Leakage-Free Evaluation

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Abstract

Deep-learning fault classifiers and locators for transmission lines are often evaluated on unvalidated simulations, with possible data leakage and without comparison against the impedance-based methods used in practice. This study builds an exact time-domain simulator of a 400 kV, 200 km two-source line, whose fault currents agree with symmetrical-component calculations within 2%, and generates 22,600 independent scenarios covering ten fault types, fault resistance, location, inception angle, loading and source strength. Single-ended 25 ms windows sampled at 4 kHz were used to train one-dimensional convolutional neural networks (CNNs), which were compared with feature-based classifiers and with the reactance and Takagi locators. The CNN classified faults with 99.91% accuracy in 0.4 ms per window, but feature-based classifiers were equally accurate, and all learned classifiers failed for fault resistances beyond the training range until that range was included in training, which in turn increased false alarms under strong noise. CNN regression located faults with a mean absolute error of 5.81 km, better than other learned models but far worse than the Takagi method on the third post-fault cycle. A hybrid scheme, in which the CNN supplies the fault type and the Takagi method the distance, reduced the error to 1.40 km, located 93.8% of faults within 2% of the line length, and remained accurate for weak sources, noise and high fault resistance. Deep learning is thus best used for fast classification, and physics-based methods for precise location.

Keywords: Fault classification; fault location; transmission line; convolutional neural network; Takagi method; power system protection

1. Introduction

Short-circuit faults are the most frequent disturbances on overhead transmission lines. The protection system must detect the fault, identify the faulted phases and disconnect the line within a few cycles, and the fault must then be located so that crews can repair the line quickly. Classification thus serves fast protection decisions such as single-pole tripping, whereas location serves restoration (Lima et al., 2022; Shakiba et al., 2023). Classical one-ended locators estimate the impedance to the fault from voltage and current phasors; the method of Takagi et al. (1982) uses the fault-induced (superimposed) current to suppress the effect of fault resistance and load flow. These methods need no training data, but their accuracy depends on reliable phasors, correct fault-type selection and assumptions about the remote infeed (Akhavan & Yazdaninejadi, 2026; Das et al., 2014). Machine-learning and deep-learning models have therefore been proposed to learn the mapping from waveforms to fault type and distance directly (Rezapour et al., 2023; Shakiba et al., 2023).

Significance and problem statement:

Reported accuracies of learned fault classifiers often exceed 99% (Akter et al., 2024; Nayak et al., 2024; Ogar et al., 2022), but they are usually obtained on simulated data whose generation is not validated, with test conditions drawn from the training ranges, and without comparison against the impedance-based methods used in practice. If windows from the same simulation enter both training and test sets, the evaluation can also leak information (Kapoor & Narayanan, 2023). It therefore remains unclear whether a deep network is preferable to a simple feature-based classifier, how it behaves outside its training range, and whether it locates faults better than a classical locator.

Objectives and contributions:

This study answers these questions with a reproducible protocol and makes four contributions: (i) an exact time-domain simulator of a 400 kV, 200 km two-source line, validated against symmetrical-component calculations; (ii) compact one-dimensional convolutional neural networks (CNNs) for fault classification and location, evaluated with feature-based benchmarks on scenario-independent test sets that include high fault resistance, weak sources and noise; (iii) a comparison of the learned locators with the reactance and Takagi methods on the same window, on later post-fault data and with ideal phasors; and (iv) a hybrid scheme in which the CNN supplies the fault type within one cycle and the Takagi method computes the distance from the third post-fault cycle.

2. Literature Review

Reviews document a rapid growth of machine-learning methods for transmission-line fault diagnosis, from decision trees, random forests and support vector machines (SVMs) to convolutional and recurrent networks (Shakiba et al., 2023), with a similar trend for distribution networks (Rezapour et al., 2023). Feature-based studies report high accuracies, for example 99.54% with a CatBoost classifier on a simulated 330 kV line (Ogar et al., 2022), improved accuracy with a genetically optimised multiple-SVM model (Sun et al., 2023), and interpretable soft-voting ensembles on PMU

data (Akter et al., 2024). Deep-learning studies apply two-dimensional CNNs to wavelet scalograms with accuracies above 99.6% at 20 dB noise (Nayak et al., 2024), LSTM autoencoders for unsupervised diagnosis (Hossain et al., 2026), CNN–LSTM–attention fusion for two-terminal location (Su et al., 2023), hierarchical deep-learning frameworks on PMU data (Shadi et al., 2022) and wide neural networks for precise location (Yuvaraju et al., 2024). Low-latency neural detection (Ogar et al., 2023) and embedded travelling-wave location in about one millisecond (Jiménez-Aparicio et al., 2022) show that such models can run on relay hardware.

Classical location methods also continue to evolve: impedance-based techniques are reviewed in Das et al. (2014), recent one-ended methods estimate the remote-source impedance (Akhavan & Yazdaninejadi, 2026), robust DFT phasor estimation reduces errors caused by decaying DC components (Liang et al., 2022), and travelling-wave methods offer high accuracy at the cost of high sampling rates (Mishra et al., 2023). High-impedance faults remain difficult for all approaches (Sinha et al., 2023), generalisation to other lines has been addressed with transfer learning (Shakiba et al., 2022), and public simulation frameworks (Kouraichi et al., 2026) and explainable machine learning (Machlev et al., 2022) aim at more transparent studies. Three gaps remain: the simulation models behind most datasets are not validated, learned models are rarely tested outside their training ranges, and learned locators are seldom compared with classical locators that use the same measurements and the longer data windows available after the protection has acted.

3. Methodology

3.1 Test System and Simulation Model

The test system (Figure 1, Table 1) consists of a 400 kV, 50 Hz, 200 km transmission line between two Thevenin sources. The relay at bus S measures the three phase voltages and the three line currents. The line is represented by 20 coupled three-phase π -sections. Each section has series resistance and inductance matrices and a shunt capacitance matrix, which are obtained from the zero- and positive-sequence parameters as

$$\mathbf{Z} = \begin{bmatrix} Z_s & Z_m & Z_m \\ Z_m & Z_s & Z_m \\ Z_m & Z_m & Z_s \end{bmatrix}, \quad Z_s = \frac{Z_0 + 2Z_1}{3}, \quad Z_m = \frac{Z_0 - Z_1}{3} \quad (1)$$

Table 1. Parameters of the simulated transmission system

Quantity	Value
Nominal voltage / frequency	400 kV (line-to-line) / 50 Hz
Line length / model	200 km / 20 coupled three-phase π -sections
Positive-sequence R, L, C per km	0.028 Ω , 1.034 mH, 11.4 nF
Zero-sequence R, L, C per km	0.275 Ω , 3.28 mH, 7.75 nF
Sources S and R	short-circuit level 5–25 GVA, X/R 10–20, Z_0/Z_1 1–3
Source voltages / load angle δ	0.95–1.05 p.u. / -25° to $+25^\circ$

Quantity	Value
Relay measurements	v_{abc}, i_{abc} at bus S, 4 kHz (80 samples/cycle)
Base quantities	326.6 kV peak phase voltage; 2,041 A peak current (1,000 MVA)

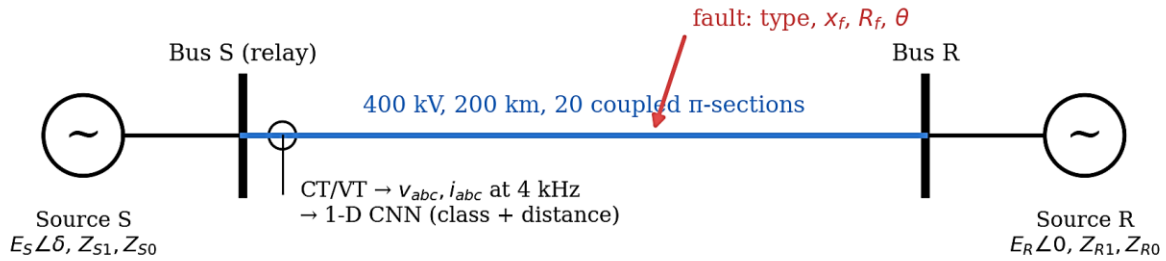


Figure 1. Single-line diagram of the simulated two-source 400 kV transmission system

With the series-branch currents and node voltages collected in the state vector $\mathbf{x}$, the network obeys the linear state equation

$$\mathbf{M} \frac{d\mathbf{x}}{dt} = \mathbf{A} \mathbf{x} + \mathbf{B} \mathbf{e}(t) \quad (2)$$

where $\mathbf{M}$ contains the inductance and capacitance matrices, $\mathbf{A}$ the resistances, conductances and incidence relations, and $\mathbf{e}(t)$ the sinusoidal source voltages. A fault of type k with resistance R_f at distance x_f is represented by a node placed at x_f and a star-connected conductance network between the faulted phases and ground. With phase conductances $\mathbf{g}$ and ground conductance g_g , the fault adds the conductance matrix

$$\mathbf{G}_f = \text{diag}(\mathbf{g}) - \frac{\mathbf{g} \mathbf{g}^T}{\mathbf{1}^T \mathbf{g} + g_g} \quad (3)$$

to the fault node. Single-phase-to-ground faults use R_f to ground, phase-to-phase faults use R_f between the phases, double-phase-to-ground faults use R_f to ground, and three-phase faults use $R_f/2$ per phase. Because the network is linear between switching instants, the post-fault response is computed exactly as the sum of the new phasor steady state $\mathbf{X}_1$ and a transient that decays with the matrix exponential:

$$\mathbf{x}(t) = \text{Re}\{\mathbf{X}_1 e^{j\omega t}\} + e^{\mathbf{M}^{-1} \mathbf{A}_1 (t-t_0)} [\mathbf{x}(t_0) - \text{Re}\{\mathbf{X}_1 e^{j\omega t_0}\}] \quad (4)$$

where t_0 is the inception instant and $\mathbf{x}(t_0)$ the pre-fault steady state. This formulation avoids numerical integration errors and the artificial oscillations that stiff fault conductances cause in fixed-step integrators. The response is evaluated at 20 kHz, averaged over five samples as a simple anti-aliasing filter, and decimated to 4 kHz, which corresponds to the 80 samples per cycle of IEC 61850 sampled-value streams in digital substations (Lima et al., 2022).

3.2 Validation of the Simulation

Two independent checks were performed (Table 2). First, the steady-state fault current at the relay was compared with a symmetrical-component calculation that neglects line capacitance, for bolted single-phase, phase-to-phase, double-phase-to-ground and three-phase faults at 25, 100 and 175 km; Table 2 lists the 175 km cases, which showed the largest deviations. The deviation did not exceed 2.0%, and the largest deviations occurred for remote faults, where the neglected line capacitance matters most. Second, the full-cycle DFT of the simulated waveform in the tenth post-fault cycle agreed with the network phasor to within 0.05%, which confirms that the transient solution converges to the correct steady state. Figure 2 shows a typical single-phase-to-ground fault at 100 km with a fault resistance of 5Ω : the faulted-phase voltage collapses, the fault current contains a decaying DC offset, and high-frequency oscillations caused by the line capacitance appear immediately after inception.

Table 2. Validation of the simulated faulted-phase current magnitude at the relay for bolted faults at 175 km (p.u. of 2,041 A peak)

Fault	Location (km)	Symmetrical components (p.u.)	Network phasor (p.u.)	Time-domain DFT (p.u.)	Deviation (%)
AG	175	1.469	1.439	1.439	-2.00
BC	175	2.040	2.026	2.026	-0.65
BCG	175	2.099	2.080	2.080	-0.90
ABC	175	2.190	2.170	2.169	-0.93

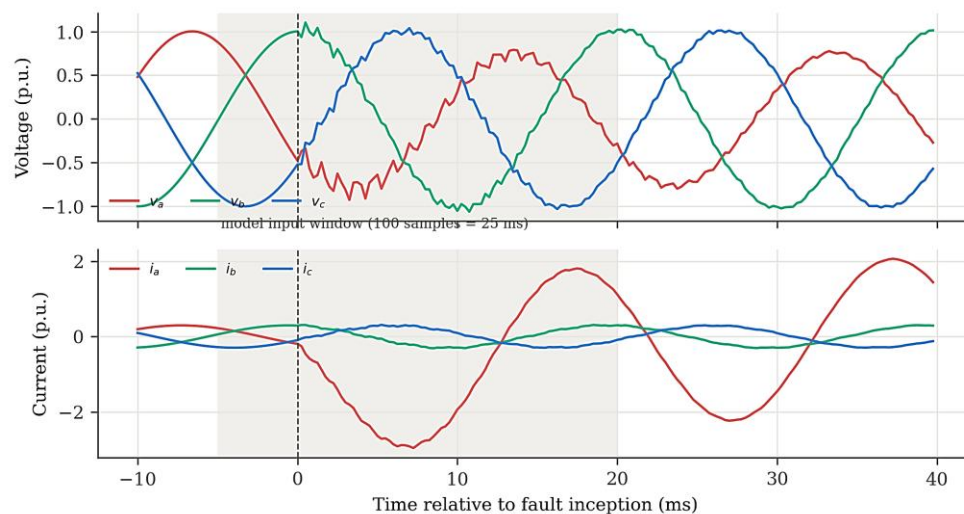


Figure 2. Relay voltages and currents for a phase-A-to-ground fault at 100 km with $R_f = 5 \Omega$; the shaded area marks the 25 ms model input window

3.3 Dataset Generation and Leakage-Free Partitioning

Each scenario draws the class (ten shunt fault types or no fault), the fault distance (2–198 km), the fault resistance (log-uniform, 0.1–100 Ω), the inception angle (0–360°) and the load angle, source voltages, strengths and impedance ratios from the ranges in Table 1, and yields exactly one 100-sample (25 ms) window of the six relay signals, with the inception between samples 15 and 25. Because each simulation produces one window and every subset was generated with its own random seeds, no scenario can contribute to more than one subset (Table 3). Two extrapolation sets contain fault resistances of 100–300 Ω and weak sending-end sources of 1.5–4 GVA. White Gaussian noise was added to each channel with a standard deviation set by the signal-to-noise ratio (SNR),

$$\sigma_c = \frac{\text{RMS}(x_c)}{10^{\text{SNR}/20}} \quad (5)$$

with a random SNR of 30–60 dB during training and fixed SNRs of 40, 30 and 20 dB, or no noise, during testing.

Table 3. Composition of the simulated datasets (each subset balanced over its classes)

Set	Fault resistance	Sending-source level	Scenarios	Purpose
Training	0.1–100 Ω	5–25 GVA	12,100	model fitting
Validation	0.1–100 Ω	5–25 GVA	2,200	early stopping, model selection
Test	0.1–100 Ω	5–25 GVA	3,300	in-distribution evaluation
High resistance	100–300 Ω	5–25 GVA	1,500	extrapolation in R_f
Weak source	0.1–100 Ω	1.5–4 GVA	1,500	extrapolation in system strength
Extended training / validation	100–300 Ω	5–25 GVA	3,000 / 600	remedy experiment (Section 4.1)

3.4 Proposed Convolutional Networks

The proposed networks (Figure 3) take the 100×6 window, standardised with training-set statistics, as input. Three one-dimensional convolutional layers with 32, 64 and 64 filters, kernel sizes 7, 5 and 3 and ReLU activation extract local waveform features such as the voltage collapse, the current step and the DC offset; two max-pooling layers halve the time resolution, and global average pooling makes the representation independent of the exact inception instant. A dense layer of 64 units with dropout (rate 0.2) forms the shared representation. The classification head outputs the probabilities of the eleven classes through a softmax, and the location head estimates the normalised distance x_f/L through two dense layers. Three configurations were trained: a classification-only CNN, a location-only CNN, and a multi-task CNN that shares the trunk and minimises

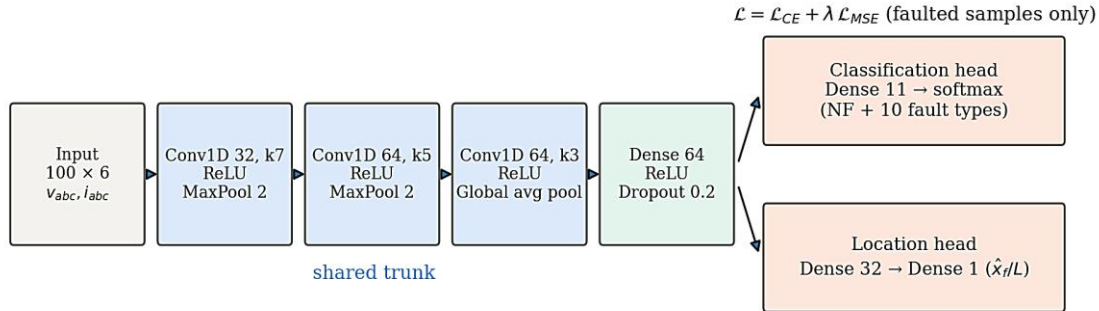


Figure 3. Architecture of the proposed one-dimensional CNN; the classification-only and location-only variants keep one of the two heads

$$\mathcal{L} = -\frac{1}{B} \sum_{n=1}^B \log p_{n,y_n} + \lambda \frac{\sum_n m_n (\hat{d}_n - d_n)^2}{\sum_n m_n} \quad (6)$$

where m_n is 1 for faulted samples and 0 otherwise, $d_n = x_f/L$ and $\lambda = 50$ balances the two terms. All layers, including back-propagation, were implemented in NumPy, and the analytical gradients were verified against finite differences (maximum relative error 3×10^{-9}).

3.5 Benchmark Methods

Three feature-based classifiers and two feature-based regressors were trained with scikit-learn (Pedregosa et al., 2011) on 24 features extracted from the same window: the full-cycle DFT phasors of the last 80 samples (magnitudes and real and imaginary parts referred to the phase-A voltage), the magnitudes of the zero-, positive- and negative-sequence voltages and currents, and the zero- and negative-to-positive-sequence current ratios. The DFT phasor of channel c is

$$X_c = \frac{2}{N} \sum_{n=0}^{N-1} x_c[n] e^{-j2\pi n/N}, \quad N = 80 \quad (7)$$

The classifiers were an MLP with two hidden layers (128 and 64 units), a random forest with 300 trees and an SVM with a radial basis function kernel ($C = 10$); the regressors were an MLP and a random forest of the same sizes. As classical locators, the reactance method and the Takagi method (Takagi et al., 1982) were implemented with zero-sequence compensation for ground faults and the appropriate phase-to-phase loop for the other faults. For a loop voltage V , loop current I and superimposed current $\Delta I = I - I_{\text{pre}}$, the Takagi estimate of the distance is

$$\hat{x}_f = \frac{\text{Im}\{V \Delta I^*\}}{\text{Im}\{z_1 I \Delta I^*\}} \quad (8)$$

where z_1 is the positive-sequence line impedance per kilometre and the pre-fault current I_{pre} is taken from the relay memory. The classical locators were given the true fault type in the benchmark evaluation, which favours them, and they were applied to three kinds of phasors: the DFT of the same

25 ms window used by the learned models, the DFT of the third post-fault cycle (40–60 ms after inception), and the exact steady-state phasors, which give an upper bound on their accuracy.

3.6 Proposed Hybrid Scheme

The hybrid scheme assigns each task to the method that suits it. The classification CNN decides the fault type from the first 25 ms, which is fast enough for protection functions such as phase selection. The fault type then selects the measuring loop of the Takagi method, which computes the distance from the third post-fault cycle, i.e., before a typical breaker clears the fault after three to five cycles. If the CNN predicts no fault, no distance is reported. In contrast to the benchmark evaluation of the classical locators, the hybrid scheme uses the predicted rather than the true fault type.

3.7 Training and Evaluation Protocol

The networks were trained with the Adam optimiser (learning rate 10^{-3} , mini-batches of 128, weight decay 10^{-4} , gradient clipping at norm 5); the learning rate was halved after four epochs without validation improvement, and training stopped after twelve such epochs or 80 epochs, restoring the best parameters. Every stochastic model (each CNN, the MLP and the random forest) was trained with three seeds (42, 7 and 123); the tables report the mean $\pm$ standard deviation of single runs and the seed ensemble obtained by averaging the predictions. Classification is assessed by accuracy and macro-F1 score, and location by the mean absolute error (MAE), root-mean-square error, 95th percentile and the share of faults within 1% and 2% of the line length. On a two-core CPU without GPU, a training run took about 5 min for the classifier and 3 min for the locator.

4. Results and Discussion

4.1 Fault Classification

Table 4 summarises the classification results. On the in-distribution test set, all methods were highly accurate. The classification CNN reached $99.93 \pm 0.03\%$ for single runs and 99.91% as an ensemble, and the random forest on phasor features reached 99.97%. The deep network therefore offered no accuracy advantage over well-designed phasor features when the test conditions matched the training conditions, which agrees with the high accuracies reported for feature-based ensembles (Akter et al., 2024; Ogar et al., 2022). Sharing one trunk between classification and location lowered the accuracy to 99.58%, so the multi-task network suffered from negative transfer between its two objectives.

Table 4. Fault classification accuracy (eleven classes). Single run: mean $\pm$ standard deviation over three seeds; other columns: seed ensembles (single model for the SVM)

Model	Single run (%)	Ensemble (%)	Macro-F1 (%)	30 dB (%)	20 dB (%)	High R _r (%)	Weak source (%)
1-D CNN classifier	99.93 $\pm$ 0.03	99.91	99.91	99.91	98.21	76.00	99.27
Multi-task CNN	99.41 $\pm$ 0.14	99.58	99.58	99.64	99.27	57.87	99.07
MLP (phasor features)	99.75 $\pm$ 0.14	99.79	99.79	99.76	99.33	72.80	99.87
Random forest	99.97 $\pm$ 0.00	99.97	99.97	99.97	94.30	91.13	99.40
SVM (RBF)	–	99.79	99.79	99.85	99.48	75.73	99.67

Measurement noise and extrapolation revealed larger differences (Figures 4 and 5). At 20 dB, which lies outside the 30–60 dB range used during training, the accuracy of the CNN fell to 98.21% and that of the random forest to 94.30%, whereas the MLP and SVM retained more than 99%. The confusion matrix in Figure 4a shows that the CNN errors at 20 dB were almost entirely false alarms: 17% of the no-fault windows were classified as three-phase faults, while every fault was still detected. For fault resistances of 100–300 Ω , all classifiers trained on 0.1–100 Ω failed to a large extent: the accuracy dropped to 76.00% for the CNN, 72.80% for the MLP and 75.73% for the SVM, and only the random forest kept 91.13%. Figure 4b shows two failure modes: high-resistance faults were mistaken for normal operation, and high-resistance double-phase-to-ground faults for phase-to-phase faults, because the ground path carries little current. Weak sources caused only small losses (Table 4), since they change the amplitudes but not the patterns of each fault type.

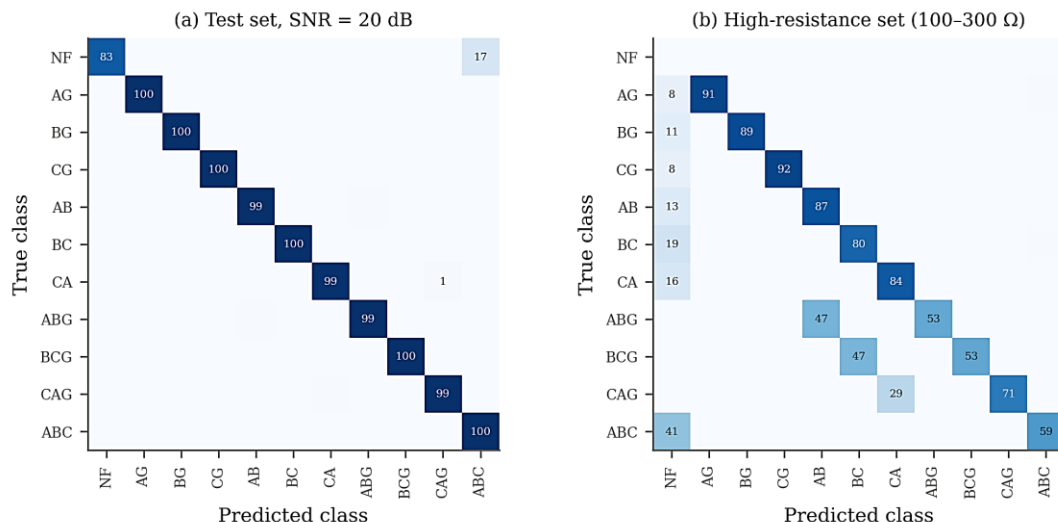


Figure 4. Confusion matrices (%) of the CNN classifier ensemble: (a) in-distribution test set at 20 dB SNR; (b) high-resistance faults (100–300 Ω) without noise

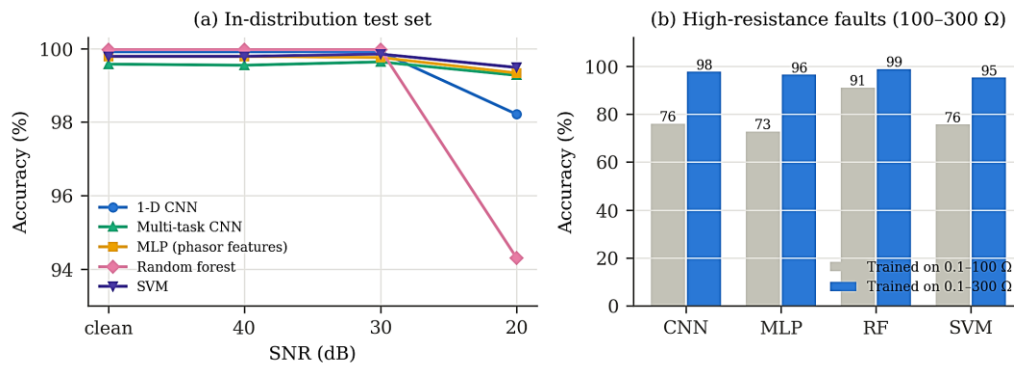


Figure 5. Robustness of the classifiers: (a) accuracy on the in-distribution test set as a function of the SNR; (b) accuracy on high-resistance faults when trained on 0.1–100 Ω and on 0.1–300 Ω

Remedy and trade-off. To test whether the failure is a matter of training coverage, all classifiers were retrained with an additional 3,000 scenarios of 100–300 Ω, generated independently of the high-resistance test set (Table 5). The accuracy on high-resistance faults then rose to 97.67% for the CNN and 98.87% for the random forest. However, the extended models became much less secure under strong noise: at 20 dB, the CNN accuracy on the original test set fell to 88.30%, because a noisy no-fault window then resembles a high-resistance fault, and every such window was flagged as a fault. Dependability for high-resistance faults and security against noise therefore conflict, and both the fault-resistance range and the noise level seen in service must be represented in the training data.

Table 5. Effect of extending the training range of the fault resistance on accuracy (%)

Model	Training R_f range	Test, clean (%)	Test, 20 dB (%)	High R_f (%)
1-D CNN	0.1–100 Ω	99.91	98.21	76.00
	0.1–300 Ω	100.00	88.30	97.67
MLP	0.1–100 Ω	99.79	99.33	72.80
	0.1–300 Ω	99.64	93.97	96.47
Random forest	0.1–100 Ω	99.97	94.30	91.13
	0.1–300 Ω	99.97	79.06	98.87
SVM	0.1–100 Ω	99.79	99.48	75.73
	0.1–300 Ω	99.82	92.94	95.27

4.2 Fault Location

Table 6 and Figure 6 compare the locators on the in-distribution test set. Within the 25 ms window, the location CNN was the most accurate method, with an ensemble MAE of 5.81 km, compared with 7.05 km for the MLP on phasor features and 7.84 km for the Takagi method applied to the same window. In this window, the decaying DC offset and high-frequency transients distort the DFT phasors (Liang et al., 2022), whereas the CNN learns to interpret the raw transient. Nevertheless, even the CNN located only 50.2% of the faults within 2% of the line length (4 km).

Table 6. Fault location accuracy on the in-distribution test set (seed ensembles; single runs in brackets as mean $\pm$ standard deviation). $\dagger$ Classical locators given the true fault type

Method	Data after inception	MAE (km)	RMSE (km)	95th pct. (km)	$\leq 1\%$ of L (%)	$\leq 2\%$ of L (%)
1-D CNN regression	1 cycle	5.81 (6.55 $\pm$ 0.92)	8.27	17.12	27.3	50.2
Multi-task CNN	1 cycle	7.41 (8.44 $\pm$ 1.09)	10.21	20.88	21.0	39.1
MLP (phasor features)	1 cycle	7.05 (7.62 $\pm$ 0.52)	10.58	22.98	25.6	46.3
Random forest (phasor features)	1 cycle	8.93 (8.95 $\pm$ 0.01)	14.00	29.30	23.2	42.1
Reactance method, same window $\dagger$	1 cycle	10.12	18.94	37.44	23.9	41.9
Takagi method, same window $\dagger$	1 cycle	7.84	13.29	23.03	24.3	43.0
Hybrid: CNN type + reactance	3 cycles	5.79	15.08	29.16	56.6	74.1
Hybrid: CNN type + Takagi (proposed)	3 cycles	1.40	5.16	4.35	81.8	93.8
Takagi, steady-state phasors (bound) $\dagger$	steady state	0.97	5.23	2.52	90.1	98.3

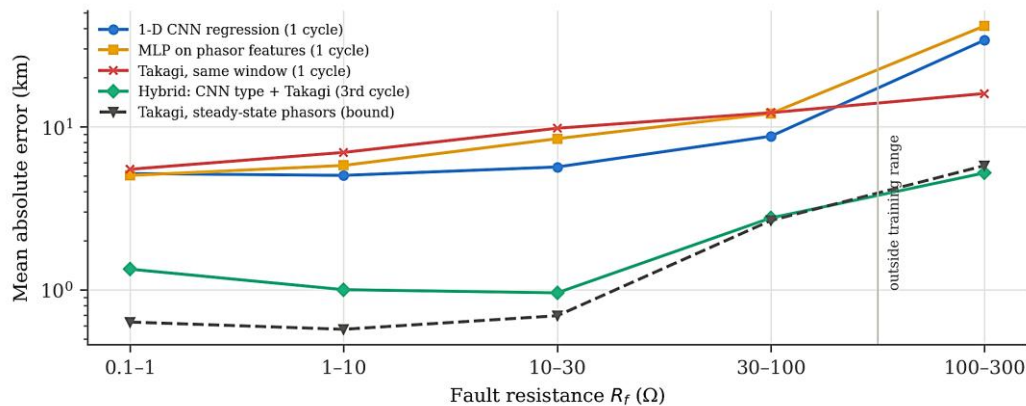


Figure 6. Mean absolute location error as a function of the fault resistance (in-distribution test set and high-resistance set); the hybrid scheme uses the CNN-predicted fault type

Given the third post-fault cycle, in which the transients have largely decayed, the Takagi method became far more accurate. In the proposed hybrid scheme, which uses the fault type predicted by the CNN, the MAE was 1.40 km, 81.8% of the faults were located within 1% and 93.8% within 2% of the line length. This is four times more accurate than the best learned locator and close to the bound of 0.97 km obtained with exact steady-state phasors. The reactance method, which ignores fault resistance and remote infeed, was much less accurate (5.79 km), which confirms the value of the superimposed-current principle of Takagi et al. (1982). The occasional large errors of the Takagi method (RMSE 5.16 km) occurred for a few faults near the remote end of the line with moderate to

high fault resistance, where the fault-induced current seen by the relay is small and the residual transient distorts the phasors.

Table 7 shows that the advantage of the hybrid scheme persists under adverse conditions. At 20 dB, its MAE rose only to 2.13 km because the DFT averages noise over a full cycle. For weak sources, the learned locators degraded strongly (CNN 13.73 km, MLP 17.91 km), whereas the hybrid scheme remained at 1.92 km, because the Takagi equation does not depend on the source strength. For high-resistance faults, the learned locators failed (33.92 km for the CNN), while the hybrid scheme achieved 5.21 km for the 88.4% of faults that the CNN detected. Physics-based location thus extrapolates where learned regression does not.

Table 7. Location robustness: MAE in km (share within 2% of L) [share of faults located when below 100%]. † True fault type given

Method	Test, 20 dB	High R_f (100–300 Ω)	Weak source
1-D CNN regression	7.59 (41.4%)	33.92 (20.1%)	13.73 (25.1%)
MLP (phasor features)	7.30 (44.9%)	41.46 (19.0%)	17.91 (17.1%)
Takagi, same window †	7.81 (42.0%)	15.98 (37.5%)	9.31 (37.1%)
Hybrid CNN + Takagi	2.13 (87.1%)	5.21 (79.6%) [88.4%]	1.92 (87.1%) [99.8%]
Takagi, steady state (bound) †	0.97 (98.3%)	5.77 (77.3%)	1.19 (94.7%)

4.3 Computational Cost

The classification CNN has 28,907 parameters and classified a single window in 0.38 ms with a plain NumPy implementation on one CPU core, i.e., in less than 2% of a power-frequency cycle, so it is compatible with protection time scales and with embedded relay hardware (Jiménez-Aparicio et al., 2022; Ogar et al., 2023). The feature-based models are even cheaper (training in 2–4 s and inference below 0.1 ms per window), and the Takagi computation requires only one DFT and one complex division.

4.4 Discussion

The results support a clear division of labour. Classification has a few discrete outcomes whose signatures, such as which phases collapse and whether zero-sequence current flows, are captured equally well by a CNN on raw samples and by simple classifiers on phasor features. Location is a continuous estimation problem governed by circuit laws: a learned regressor must disentangle transients, fault resistance, load flow and source strengths, and it extrapolates poorly when any of these leaves the training range, whereas the Takagi equation encodes the circuit law and is accurate under all tested conditions once it receives good phasors and the correct fault loop. Headline accuracies above 99% also say little about field performance, because all classifiers lost up to 42 percentage points on fault resistances three times larger than the training maximum, and widening the training range traded this dependability against security under strong noise. These findings support

calls for leakage-free evaluation (Kapoor & Narayanan, 2023) and for attention to generalisation (Shakiba et al., 2022).

The study has limitations: the data are simulated for a single, ideally transposed line with lumped π -sections and ideal instrument transformers, without current-transformer saturation, series compensation, parallel lines or arc non-linearity; the no-fault class contains no switching events; the classical locators were given the true fault type in the benchmark (the hybrid scheme used predicted types); and the network hyperparameters were not tuned systematically.

5. Conclusions and Recommendations

This study developed a validated, exact time-domain simulator of a two-source 400 kV transmission line and used it to evaluate one-dimensional convolutional networks for fault classification and location against feature-based classifiers and the classical reactance and Takagi locators under a leakage-free protocol. The CNN classified faults with 99.91% accuracy from a 25 ms window in under half a millisecond, but feature-based classifiers were equally accurate, multi-task sharing reduced accuracy, and all learned classifiers failed for fault resistances beyond the training range until that range was included, at the cost of more false alarms under strong noise. For fault location, CNN regression was the best learned method but remained four times less accurate than the Takagi method applied to the third post-fault cycle. The proposed hybrid scheme, in which the CNN selects the fault type and the Takagi method computes the distance, located faults with a mean error of 1.40 km on a 200 km line and remained accurate for weak sources, noise and high fault resistance.

Three recommendations follow. Deep learning should be used for fast fault detection and phase selection, while distance estimation should rely on physics-based methods supplied with the predicted fault type. Training data must cover the fault resistances, source strengths and noise levels expected in service, and learned protection functions should be tested on deliberately shifted data before deployment. Future work should validate the scheme with field records and hardware-in-the-loop tests, add switching events and instrument-transformer effects, extend it to series-compensated and double-circuit lines, and use DC-offset-resistant phasor estimators to shorten the time needed for accurate location.

Declarations

Data availability. The simulation, training and evaluation code and the generated datasets are available from the corresponding author on reasonable request.

Conflict of interest. The authors declare no conflict of interest.

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