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Optimizing renewable energy: advanced strategies for enhanced efficiency and sustainability

TÉCNICA DE LOCALIZAÇÃO DE FALTAS BASEADA EM MÁXIMA VARIAÇÃO TRANSITÓRIA E EM REDE NEURAL LSTM FAULT LOCATION TECHNIQUE BASED ON MAXIMUM TRANSIENT DEVIATION AND LSTM NEURAL NETWORK

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RESUMO

Em sistemas elétricos de potência, as linhas de transmissão (LTs) são componentes críticos que frequentemente estão suscetíveis a diferentes tipos de faltas. Quando ocorre uma falta, um procedimento rápido de restauração é essencial e depende da determinação precisa da localização da falta. Este estudo apresenta um novo método que combina medições da Máxima Variação Transitória Absoluta (AMTD) com Redes Neurais do tipo Long Short-Term Memory (LSTM) para localização de faltas em LTs. A definição da topologia LSTM mais adequada é discutida, e o processo de treinamento é detalhado para identificar a melhor configuração para executar a tarefa desejada. Os casos simulados de faltas e o algoritmo baseado em AMTD foram modelados e executados utilizando o Simulador Digital em Tempo Real (RTDS), permitindo simulações em tempo real. Os resultados demonstram que o método desenvolvido é preciso para localização de falhas em LTs, independentemente das características da falha.

Palavras-chave: Localização de Falhas, Proteção de Sistemas de Potência, MTD, Rede Neural, Simulação em Tempo Real.

ABSTRACT

In electrical power systems, transmission lines (TLs) are critical components that are often susceptible to different types of faults. Once a fault occurs, a fast restoration procedure is crucial and depends on accurately determining the fault location. This study introduces a novel method that combines Absolute Maximum Transient Deviation (AMTD) measurements and Long Short-Term Memory (LSTM) Neural Networks for fault location in TLs. The definition of the most suitable LSTM topology is discussed, and the training process is elaborated to identify the best configuration for performing the desired task. The simulated fault cases and the AMTD-based algorithm were modeled and executed using the Real-Time Digital Simulator (RTDS), enabling real-time simulations. The results demonstrate that the developed method is accurate for fault location in TLs, regardless of fault characteristics.

Keywords: Fault Location, Power System Protection, MTD, Neural Network, Real-Time Simulation.

1 INTRODUCTION

Fault location in transmission lines (TLs) is essential for the operation and maintenance of electrical systems, as fast and accurate identification enables rapid service restoration [1]. In Brazil, the National Electric System Operator (ONS) monitors TL performance and defines operating ranges as normal, alert, or unsatisfactory. Inaccurate fault location reduces system availability, which is critical given the role of TLs in linking generation and large consumption centers.



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Several methods have been proposed, mainly impedance-based, traveling wave, and artificial intelligence (AI) approaches [2]. Impedance methods, such as the reactance, Takagi, and negative-sequence impedance techniques, are the most common due to their simplicity, but their accuracy depends on TL parameters [3].

AI-based approaches, particularly deep learning (DL), have gained attention. In [2], the authors propose an LSTM-based method using post-fault current and voltage signals measured at one TL terminal. Results with the FADb dataset show high accuracy, although performance decreases for faults near the measurement point. Traveling-wave approaches have also shown promise: [3] use magnetic field-induced waves on a 400 kV line, demonstrating low dependence on TL parameters, while [4] apply Hausdorff distance to distinguish internal from external faults, with robust results under varying fault resistances. Hybrid methods have also been studied; [5] combine CEEMDAN decomposition with LSTM, showing high accuracy even with distributed generation.

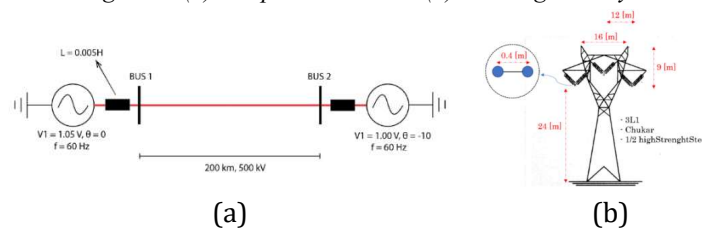
Building on these advances, this paper proposes a new fault location method for TLs, combining AMTD with LSTM. By exploiting the similarity of fault signals through AMTD and the approximation capability of LSTM, the method achieves robust and accurate performance across diverse fault scenarios.

2 METHODOLOGY

2.1. SEP adopted

For the development of the AMTD-based method, a TL of 500 kV and 200 km was modelled, assuming frequency-dependent distributed parameters, as illustrated in Figure. 1 (a). The tower geometry is depicted in Figure. (b). The Electric Power System (EPS) was modelled in RSCAD and executed in RTDS, which allows real-time simulations. Several cases were carried out considering different scenarios, including fault and normal operating conditions. During the simulations, voltage and current signals were carefully recorded.

Figure 1. (a) Adopted TL model. (b) Tower geometry.

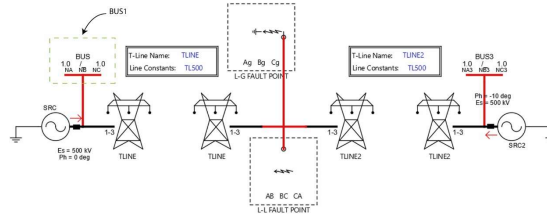


2.2. Data acquisition

The simulation of each planned case and the acquisition of voltage and current signals were carried out automatically using a routine developed in C within RSCAD. The EPS executed in the RTDS is shown in Fig. 2. The current and voltage signals were measured at the local terminal of the LT with a sampling frequency of 20 kHz, as highlighted in Fig. 2 (BUS 1). TL was divided into two variable sections, and a “fault block” was included in the model. As a result, different types of faults could be applied at various locations along the TL.



Figure 2. Power System modelled in RSCAD



2.3. AMTD algorithm

According to IEC 60050, the Maximum Transient Deviation (MTD) is the percentage difference between the final and initial steady-state values of a step response. In this study, the concept is extended to the Absolute MTD (AMTD), defined as the maximum absolute error between two consecutive semi-cycles of voltage or current signals.

As illustrated in Fig. 4(a), one full cycle of a generic voltage signal is considered. The second semi-cycle is stored, inverted, and compared with the first semi-cycle, as shown in Fig. 4(b). In steady-state conditions, the AMTD is ideally zero, as depicted in Fig. 4(c). For non-fault cases, AMTD remains close to zero, except for minor deviations due to transducer imperfections or small operational transients. By analysing AMTD patterns of voltage and current signals in each phase, it is possible to identify disturbances and estimate the fault distance.

Fig. 4. (a) One voltage cycle - EPS in normal condition (b) Comparing two half-cycles - EPS in normal condition (c) AMTD considering the EPS in normal condition

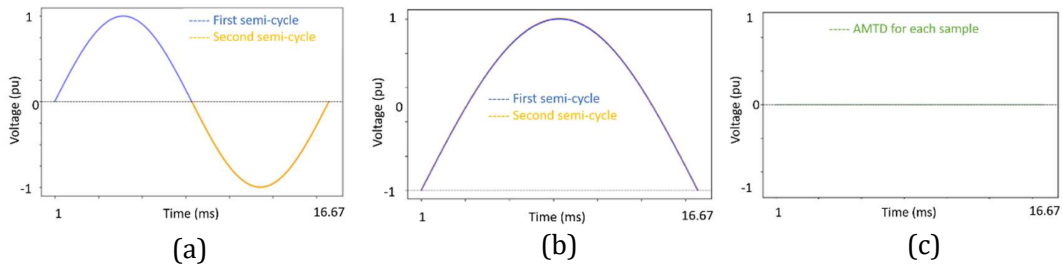
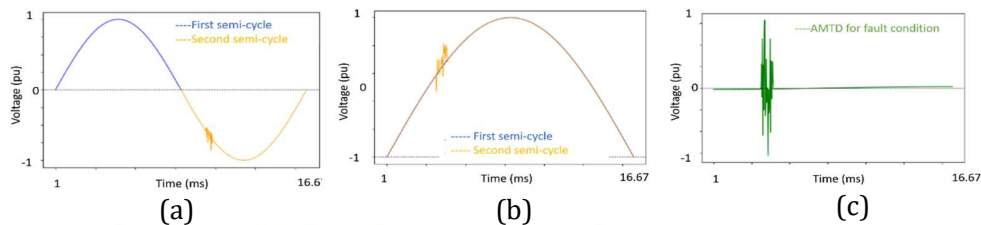


Fig. 5 (a) shows a generic voltage signal for a fault in the TL. It is observed that, when a fault occurs, the inversion of the second half-cycle does not overlap with the first half-cycle, as shown in Fig. 5 (b). Thus, for fault cases, the AMTD is non-zero, as illustrated in Fig. 5 (c).

Fig. 5. (a) Voltage signal for fault condition (b) Overlap of semi-cycles under fault condition (c) AMTD for fault condition



To perform the calculation of the AMTD between the half-cycles, a simple mathematical formulation was used. The vector V_1 is $V_1 = [v_1[1] \ v_2[2] \ \dots \ v_1[n]]$ defined as the voltage samples of the first half-cycle and V_2 is $V_2 =$



$[v_2[1] \ v_2[2] \ \dots \ v_2[n]]$ defined as the vector with voltage samples of the second half-cycle. The transient deviation (TD) vector is calculated by taking the difference between the samples of V_1 and V_2 . Thus, the TD is defined by (4):

$$TD = V_1 - V_2 \quad (1)$$

$$TD = [v_1[1] - (-v_2[1]) \ \dots \ v_1[n] - (-v_2[n])] \quad (2)$$

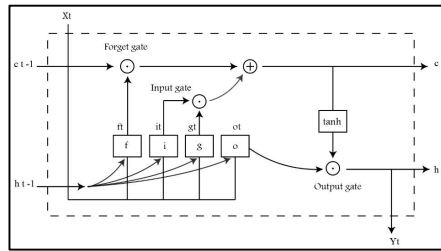
$$TD = [(v_1[1] + v_2[1]) \ \dots \ (v_1[n] + v_2[n])] \quad (3)$$

$$AMTD = \text{Max} [TD] \quad (4)$$

2.4. Long Short-Term Memory Neural Network

LSTM networks are a specialized type of recurrent neural networks (RNNs), designed to handle sequential data. RNNs use hidden states and loops to store past information, allowing the output to depend on both current and previous inputs. They have two sets of weights learned during training. However, simple RNNs struggle with long-term dependencies due to vanishing or exploding gradients, which limit their effectiveness. LSTMs address this issue by incorporating mechanisms that preserve information over longer sequences.

Fig. 6. LSTM model



Considering the LSTM model presented in Fig. 8, the forget gate is used to determine how much of the previous state should be retained or forgotten. It generates a value between 0 and 1 using the sigmoid function, where 0 would mean completely forgetting, while 1 would mean completely retaining the previous information. This is represented by (5).

$$f_t = \sigma(f \cdot [h_{t-1} \ x_t] + b_f) \quad (5)$$

The input gate controls the amount of information that will be stored in the current cell state C_t . Like the forget gate, this block also uses the sigmoid function, but to determine the amount of information to be stored.

$$i_t = \sigma(i \cdot [h_{t-1} \ x_t] + b_i) \quad (6)$$

Based on the previous input and output, candidates for updating the cell state must be selected. This is done using (7) through the hyperbolic tangent function, which creates values between -1 and 1. The magnitude and direction of these values indicate what should be added to the cell state.

$$\tilde{c}_t = \tanh(g \cdot [h_{t-1} \ x_t] + b_c) \quad (7)$$

The output gate controls the amount of information from the cell state C_t that goes to the output. The output gate determines how much of the current cell state will be passed as output. This is defined by the sigmoid function according to (8).



$$o_t = \sigma(o \cdot [h_{t-1}] + b_o) \quad (8)$$

The update of the cell state occurs based on the forget gate and the output gate. Equation (9) combines these two pieces of information. Finally, the output is updated, which is a function of o_t and C_t as indicated by (10).

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \quad (9)$$

$$h_t = o_t \odot \tanh(C_t) \quad (10)$$

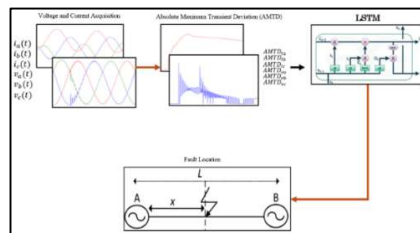
Where:

- x_t is the input vector at time t ;
- h_{t-1} is the hidden state at the previous time;
- C_{t-1} is the cell state at the previous time;
- f_t, i_t, o_t are the vectors of the forget, input, and output gates, respectively;
- $\tilde{C}_t$ is the candidate cell vector;
- f, i, C, o are the weight matrices;
- b_f, b_i, b_C, b_o are the bias vectors;
- σ is the sigmoid function.

2.5. Fault location method based on AMTD

The proposed method for fault location in TL is presented in Fig. 7. The three-phase voltage and current signals are sampled at the BUS 1, as illustrated in Figure. 7. The sampled values are then sent to the block responsible for calculating the AMTD, where the six maximum values of each variable are extracted and stored. As observed, three of these values correspond to the AMTD for current signals, and the other three correspond to the maximum AMTD for voltage signals.

Fig. 7. Proposed method for fault location



The main premise is that the AMTD values vary according to the fault distance and characteristics, with a unique combination of values for each specific fault, allowing the estimation of the fault location. In other words, this combination of AMTDs functions as a fault signature corresponding to a specific fault location. Thus, the six maximum AMTD values are fed into the LSTM neural network, which has been previously trained to associate this set of values with the corresponding fault point.



2.6. Fault Cases and Simulations

To evaluate the proposed fault location method, a large number of fault cases were carefully prepared in RSCAD and executed in RTDS, with the method implemented using the RSCAD math library. It is important to mention that the simulations were executed, assuming only single-phase faults, as they are the most common type of fault in TLs.

Conducting simulations with RTDS is essential for analyzing modern electrical systems. RTDS enables the accurate reproduction of real operating conditions in a controlled environment, which is crucial for testing and validating new protection methods and control systems without direct intervention in real systems, thereby avoiding the risks and costs associated with potential failures. Therefore, the initiative to model and evaluate the AMTD algorithm in RTDS emerges as a promising alternative for developing and testing new protection methods, particularly with regard to hardware implementation and hardware-in-the-loop (HIL) simulations. In this way, the method can be tested efficiently and reliably, enabling an accurate comparison with other methods and clearly highlighting the cost-benefit of the proposed approach. Table I shows the range of parameter variations used to generate the test cases for the adopted system.

Table 1. Parameters variations to generate the fault cases

<i>Parameters</i>	<i>Values</i>
Fault Resistance (Ω)	0.1; 1; 10; 50; 70; 100
Fault Type	AG
Angle of incidence ($^\circ$)	30; 45; 60; 90
Fault Distance (km)	15%-80% (1 km step)

For training and testing, 1,300 fault cases were generated in RSCAD and executed in RTDS using an automated routine written in C.

3 RESULTS AND DISCUSSION

3.2 LSTM training and evaluation

In an attempt to define the best LSTM configuration for implementing the fault location method, five different options were trained and tested, as shown in Table 2. As can be seen, these options differ in terms of the number of layers and neurons per layer, but all of them were subjected to the same training set.

Table 2. Neural Networks trained

Neural Network	Layer 1	Layer 2	Layer 3	Final Layer
LSTM1	500 neurons	-	-	1 neuron
LSTM2	200 neurons	-	-	1 neuron
LSTM3	200 neurons	-	200 neurons	1 neuron
LSTM4	200 neurons	200 neurons	-	1 neuron
LSTM5	200 neurons	200 neurons	100 neurons	1 neuron

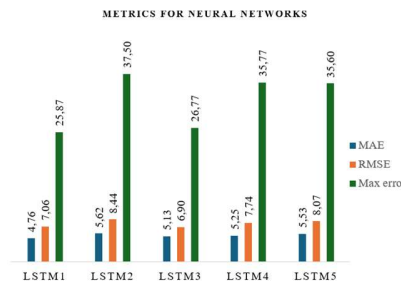
3.3 Results of LSTM neural network

The metrics MAE, RMSE, and Max Error are widely used to evaluate regression models. MAE represents the average absolute error and is easy to interpret but less sensitive to large deviations, while RMSE penalizes larger errors more strongly. In this study, these three metrics were applied.



As shown in Fig. 8, LSTM1 achieved the best results, with the lowest MAE (4.76), RMSE (7.06), and Max Error (25.87), indicating superior accuracy. LSTM2 had the worst performance, with MAE (5.62), RMSE (8.44), and Max Error (37.50). LSTM3 presented balanced results (MAE 5.13, RMSE 6.90), slightly inferior to LSTM1. LSTM4 showed similar performance (MAE 5.25, RMSE 7.74), but with a high Max Error (35.77). LSTM5 performed close to LSTM2, with MAE (5.53), RMSE (8.07), and Max Error (35.60). Overall, LSTM1 stands out as the best model, while LSTM2 and LSTM5 are the least accurate.

Fig. 8. Metrics for the tested LSTMs

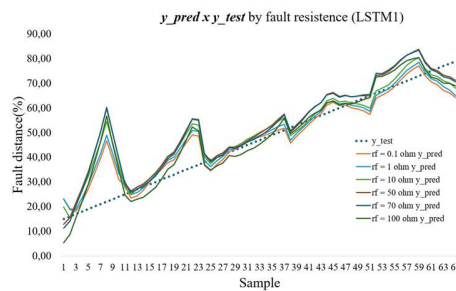


3.4 Evaluating the proposed method with the LSTM1

To evaluate the proposed fault location method, 65 new fault cases were generated, considering various fault locations and fault resistances. The expected (dotted line) and predicted fault distances for each case are shown in Fig. 15, plotted as a function of fault resistance (represented by specific colors). One way to improve the method's performance and reduce errors related to the two mentioned cases would be to include additional training cases with similar characteristics in the training set.

Regarding the cases with higher errors, this issue could likely be addressed by adjusting the hyperparameters and/or increasing the training set with new fault cases, which will be the next step of this study. However, it is worth noting the potential of the presented solution, which accurately estimates the fault distance, regardless of fault resistance (FR), for most assumed fault cases.

Fig. 8. Expected vs predicted fault location as a function of FR



3.5 Comparison with another methods

Table 3 compares different fault location methods, highlighting that the proposed method (AMTD + LSTM) combines low complexity with a wide fault resistance range, using voltage and/or current signals as input. In comparison, the methods in [1] and [2] use voltage and current simultaneously, presenting moderate complexity, relying on impedance measurements and LSTM. The method presented in [3], based on traveling wave algorithms, also shows moderate complexity and requires faster



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and more specialized measurements. Finally, the method in [4] is based on waveform similarity, operating at 500 kV with moderate to high complexity, particularly suitable for high fault resistances.

Table 3. Comparison with another methods

Reference	Proposed	[1]	[2]	[3]	[4]
Principle Operation	AMTD and LSTM	Impedance measurements	LSTM-based model	Traveling wave algorithm	Traveling wave and waveform similarity
System Tested	500 kV	110 kV	100 kV	400 kV	500 kV
Input Signals	Voltage and/or current	Voltage and current	Voltage and current	Voltage and current	Traveling wave waveforms
Fault Resistance (Ω)	0.1, 1, 10, 50, 70, and 100	100	0.01 to 100	-	10 to 500
Complexity	Low	Moderate	Moderate	Moderate	Moderate to high

4 CONCLUSIONS

This work presented a novel intelligent method for fault location in transmission lines (TL), employing an extended concept of MTD, namely Absolute MTD (AMTD), to extract a 'signature' of faulty signals, which is then associated with a fault distance using LSTM. The EPS was modelled in RSCAD and executed in RTDS, enabling real-time simulations. The procedure for developing, training, and selecting the best LSTM was detailed, with the fault location method implemented using the best option (LSTM1). An evaluation process using LSTM1 was conducted, analyzing the method's performance across various fault locations and fault resistances. Except for two cases, which will be analyzed in more detail, the obtained results were very promising, regardless of fault resistance or fault distance, demonstrating the potential of new techniques for fault location TL.

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