Real-time detection of short-circuit faults in power systems using LSTM autoencoder.

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Abstract: This paper presents a real-time detection method for short-circuit faults in meshed power networks, based on a Long Short-Term Memory (LSTM) autoencoder. The objective is to quickly and accurately identify both simple faults (single-phase, double-phase, three-phase), hybrid faults, and triple faults characterized by the simultaneous occurrence of several types of faults on different network lines. Simulations were carried out on an IEEE 9-bus system modeled in MATLAB/Simulink, covering various scenarios: faults on a single line, on two lines, and on three lines simultaneously. The results obtained show an immediate reaction of the model to disturbances, reflected by a marked increase in the loss function at the time of the incident. The system also demonstrated its ability to detect the indirect impact of faults on neighboring lines, reflecting the propagation of electrical imbalances throughout the network. These performances confirm the effectiveness and robustness of the LSTM autoencoder for intelligent, fine, and adaptive monitoring of modern power networks, fully meeting the requirements of real-time protection systems.

Keywords: Real-time detection, LSTM autoencoder, Meshed power networks, Short-circuit faults, Simple faults, Hybrid faults, Triple faults.

1 Introduction

Modern power networks, which are becoming increasingly complex and interconnected, play a crucial role in the distribution of energy worldwide. These networks are vulnerable to various types of faults, among which short circuits, which approximately 90% of contingencies are among the most frequent and damaging. A short circuit can lead to service interruptions, equipment damage, and even risks to human safety. In meshed architectures, where interconnections are numerous, a fault can spread rapidly, and multiple faults may

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even occur simultaneously on different lines of the network. This situation makes it essential to implement high-performance methods capable of rapidly identifying such faults.
Classical fault detection approaches in power networks often rely on static methods. Although these techniques are widely used, they present significant limitations in terms of responsiveness and accuracy, particularly in dynamic environments such as meshed power systems. Several techniques have been developed to detect faults in electrical networks. Some studies have employed intelligent methods but based on statistical approaches [1-3]. Other research has used autoencoders to identify anomalies but has failed to adapt to anomaly detection based on online PMU data streams [4].

In [5], he author develops a fault detection model for power distribution networks based on Long Short-Term Memory (LSTM) neural networks, aiming to effectively detect both low-impedance and high-impedance faults.

[6] Present an approach for fault detection, classification, and localization in large-scale multi-machine systems based on LSTM models. By exploiting transient signals measured by PMUs on a two-area, four-machine network, their method achieves classification accuracies above 95% and a fault location error below 0.1%.

In [7] The authors develop an approach combining an autoencoder and LSTM for the detection and diagnosis of rare faults in multivariate industrial processes. Tested on the Tennessee Eastman Process, the method achieves 96% accuracy for fault detection and 91.9% accuracy for classification, outperforming DCNN-based models.

In [8] The author presents a method based on LSTM neural networks for detecting and classifying disturbances in power quality. However, the drawback of the above-mentioned research on fault detection in electrical networks lies in their predominantly offline nature. Machine learning or deep learning models are often trained on static datasets without adaptation to evolving network conditions [9]. et, meshed power systems are inherently dynamic, with constant variations due to operational changes, leading to data drift, also known as concept drift [10]. Moreover, most research focuses on faults occurring on a single line, overlooking critical cases where multiple faults can occur simultaneously on different interconnected lines. Classical methods often fail to effectively detect hybrid or multiple faults. To overcome these limitations, our study proposes a real-time short-circuit fault detection approach in meshed networks using an LSTM autoencoder trained on the system's normal operating data. This architecture not only captures anomalies in real time but also adapts to network dynamics through its ability to model complex temporal sequences.

In offline learning, a common approach during training is to collect streaming data, preprocess it, store it in a database, and then use it to train a machine learning or deep learning algorithm. In online learning, data is continuously streamed, preprocessed, and directly fed as input to train a machine learning or deep learning algorithm [11].

2 Presentation of the LSTM autoencoder

The LSTM autoencoder is a hybrid model that combines the advantages of LSTM networks with the structure of autoencoders. The LSTM architecture relies on a memory cell capable of retaining information over time, regulating the flow of data through three main gates: input, forget, and output. Integrated into the network's hidden layers, this cell enables the effective modeling of temporal dependencies in sequential signals. The network consists of an input layer, an output layer, and multiple hidden layers equipped with recurrent connections. The LSTM architecture is shown in figure 1, as it unfolds over time. A detailed description of this architecture is provided in [12].

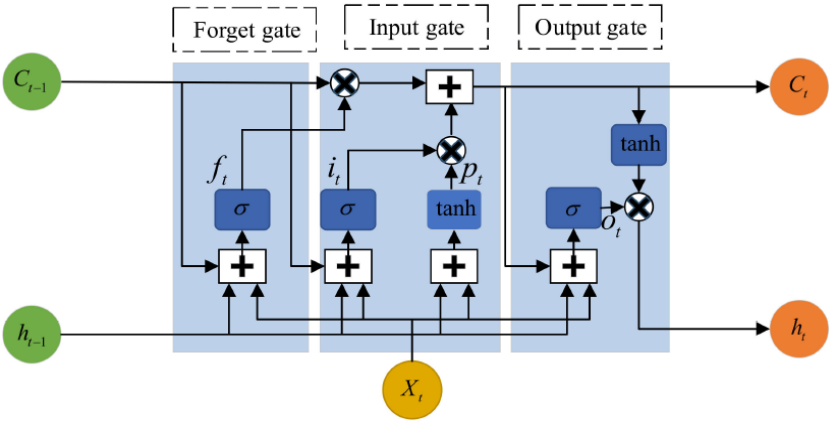

Fig. 1. LSTM network architecture.

On this basis, an LSTM autoencoder was designed to learn the normal behavior of the power network from voltage and current signals, in order to detect in real time any deviation indicative of a fault. Autoencoders are a class of deep learning algorithms composed of two components: an « encoder » followed by a « decoder ». The encoder transforms the input data X^t (which are the three-phase voltage and current values) at time step t, into a low-dimensional representation using an encoding function (equation 1).

$$g(X) = \sigma(W * X^t + b) \qquad (1) \qquad [9]$$

The decoder reconstructs the three-phase voltage and current values from the low-dimensional encoded representation z' using the decoding function (equation 2).

$$f(z') = \sigma(W * z' + b) \qquad (2) \qquad [9]$$

Figure 2 shows a simple architecture of the LSTM autoencoder.

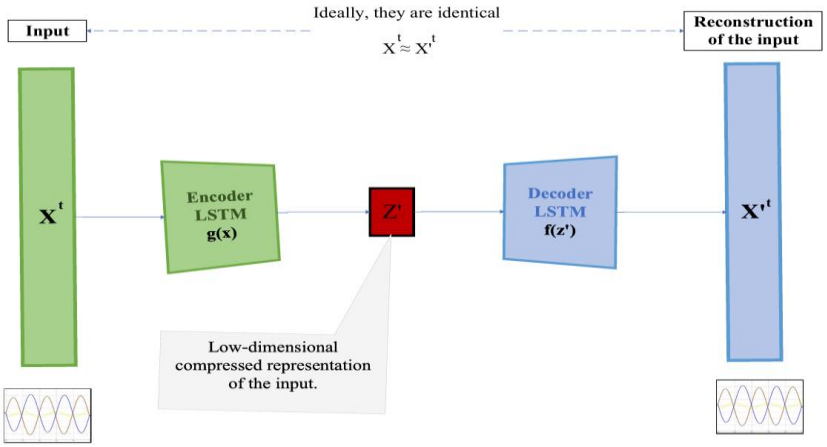

Fig. 2. Simplified architecture of the LSTM autoencoder.

Table 1 summarizes the symbols defined in Equations (1) and (2).

Table 1. Definition of symbols

Symbols	Notations
b	Bias vector
W	Weight matrix
X^t	Input feature vector, $X \in R^d$
$X'' = f(z')$	Decoded output feature vector
$\sigma(f) = \frac{1}{1+\exp(f)}$	Sigmoid activation function

This paper uses the LSTM autoencoder as a real-time anomaly detection algorithm specifically designed for time-series data. The learning objective function can be formulated as follows: given a sliding window of measurements, the LSTM encoder part of the LSTM autoencoder aims to encode the original input feature vector into a low-dimensional feature vector using an approximate mapping function $h(-)$, and the LSTM decoder part of the LSTM autoencoder aims to reconstruct/decompress the low-dimensional feature vector using $h(-)$ back into the original-dimensional feature vector, as expressed in equation (3).

$$\left[X^{(t)},.....,X^{(t+n)}\right]_{encodeur} \xrightarrow{h(-)} \left[X'^{(t)},.....,X'^{(t+n)}\right]_{decodeur} \quad (3)\ [13]$$

The LSTM autoencoder aims to minimize the reconstruction error between X and X' using the mean squared error (MSE) as the loss function, as given in equation (4).

$$MSE = \frac{1}{N}\sum_{i=1}^{n}(X_i - X'_i)^2 \quad (4)\ [13]$$

2.1 Training the LSTM autoencoder for faults detection

Anomaly detection in a three-phase power network relies on training a deep learning model capable of recognizing the system's normal behavior, so that any deviation from this behavior can be identified as potentially abnormal. To achieve this, an LSTM autoencoder was designed using the deepSignalAnomalyDetectorLSTM function in MATLAB-Simulink. The training of this network is based exclusively on data collected under normal conditions i.e., without any faults present on the lines so that any future deviation from this learned behavior is perceived as an anomaly.

Since voltage and current amplitudes can vary from one scenario to another, a normalization step is applied. This consists of dividing the signals by their standard deviation, which harmonizes the scale of the input data, facilitates the convergence of the training process, and improves the robustness of the model.

The normalized voltage and current signals are then concatenated into a single six-channel input matrix (three for voltage, three for current). This format faithfully represents the dynamics of the three-phase power network while meeting the requirements of the

deepSignalAnomalyDetector function. Specifically, this function requires that the input data be provided as a cell array, with each cell containing a matrix of dimensions $M \times N$, where M is the temporal length of the sequence and N is the fixed number of channels.

For training the LSTM autoencoder, a simple architecture is used, consisting of a single encoder layer and a single decoder layer, each containing 32 hidden units.

Training is carried out over 100 epochs using the Adam (Adaptive Moment Estimation) optimization algorithm. This algorithm combines the advantages of two classical optimization methods momentum and adaptive learning rate and enables fast and stable convergence. The choice of the Mean Squared Error (MSE) loss function is motivated by its ability to effectively quantify the difference between the decoder's reconstructed output and the original sequence, which is essential for anomaly detection, since any anomaly will cause a noticeable increase in this error. Once the training is completed, the model and its optimal parameters are saved in a .MAT file, allowing them to be reused in Simulink. When a fault occurs, the autoencoder fails to accurately reconstruct the sequence, leading to an instantaneous rise in the loss, which in turn triggers automatic fault detection. This approach enables fast and reliable detection of various short-circuit faults in complex electrical systems. A detailed representation of the LSTM autoencoder training process is shown in figure 5.

3 Presentation of the study power system

Our study power system is a closed-loop interconnected IEEE 9-bus meshed network consisting of nine buses, six transmission lines modeled in Π (Pi) configuration, three generators, three transformers, and three loads. The network model was implemented in MATLAB/Simulink. Figure 3 illustrates our IEEE 9-bus network. The network characteristics, as well as the data related to the generators, transformers, and loads, are presented in [14].

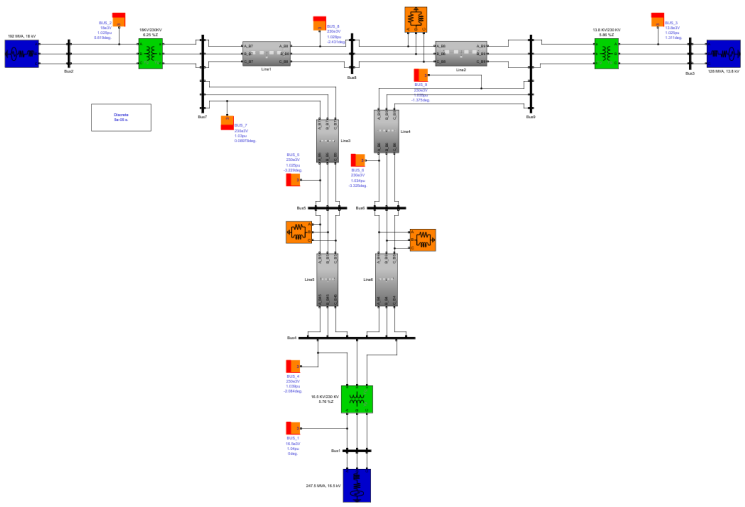

Fig. 3. Proposed IEEE 9-bus test power system model

The three-phase fault simulator is used to simulate different types of faults at various positions along the transmission line with different fault resistance values. An example of line 1 of our power network is shown in Figure 4, and the parameters of this transmission line are given in table 2.

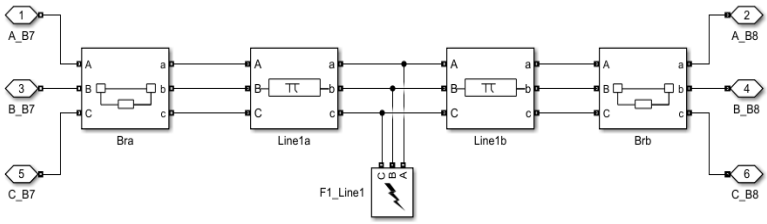

Fig. 4. Overview of line 1 in our IEEE 9-bus system.

Table 2. PI model parameters of each transmission line.

Specifications	Values
Length	100 Km
Forward system	0.01273 Ω/km
Zero-sequence system	0.3864 Ω/km
Positive-sequence inductance	0.9337e-3 H/km
Zero-sequence inductance	4.1264e-3 H/km
Positive-sequence capacitance	12.74e-9 F/km
Zero-sequence capacitance	7.751e-9 F/km

4 Application of the LSTM autoencoder for real-time fault detection

The LSTM autoencoder, trained exclusively on data corresponding to the healthy operation of the network, identifies anomalies based on the quality of signal reconstruction. In the event of a significant deviation between the input signals and their reconstruction, an anomaly is detected, in accordance with the reconstruction-based detection principle. The three-phase voltage and current signals (phases A, B, and C) are processed in real time, without intermediate storage, as illustrated in figure 5.

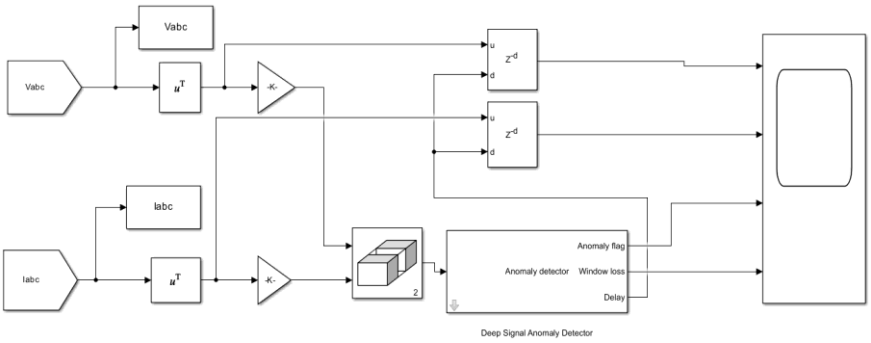

Fig. 5. Simulink model for real-time fault detection in transmission lines.

Figure 6 shows the scope visualization of the Deep Signal Anomaly Detector model. The three-phase current and voltage signals are stable and periodic, indicating the absence of disturbances in the network. Furthermore, the loss function curve remains extremely low (approaching zero) and stable throughout the simulation, confirming that the model reconstructs the signals with high accuracy. In addition, the No Fault curve, representing the detection indicator, also remains very close to zero, indicating that the triggering threshold was never exceeded. This confirms that no anomaly was detected by the system and that the network remained in a normal operating state for the entire simulation.

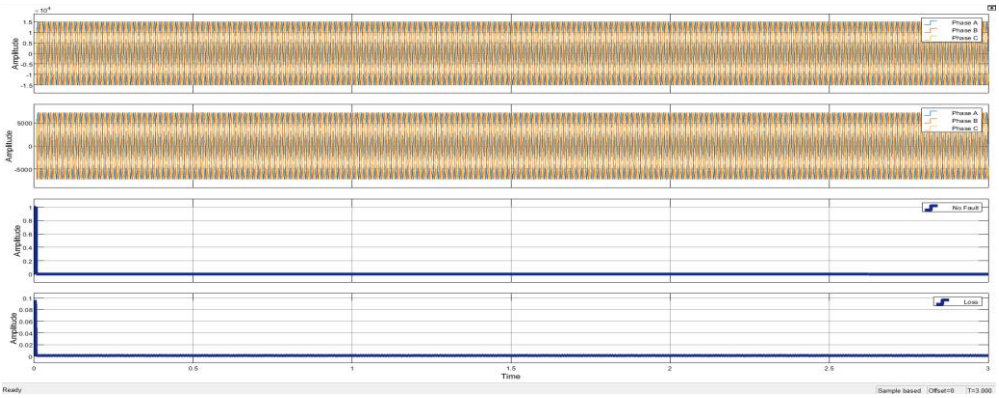

Fig. 6. Scope visualization of the Deep Signal Anomaly Detector model.

4.1 Real-time fault detection in a transmission line

In this experiment, the LSTM autoencoder was applied to the IEEE 9-bus meshed power network to evaluate its ability to detect faults in real time on a single transmission line. A single-phase A-G fault was injected on line 1 of our power system during two-time intervals: from 0.5 s to 1 s, and from 2 s to 2.5 s. Figure 7 shows the Simulink scope output obtained during this simulation.

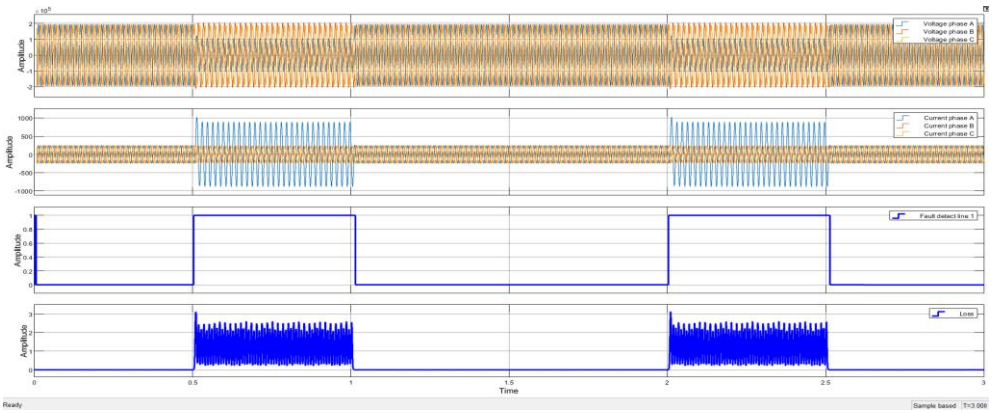

Fig. 7. Scope output for the real-time detection of an A-G fault on a single line.

4.1.1 Result analysis

The analysis of the three-phase voltage and current signals clearly shows a significant disturbance during the two relevant intervals. In particular, the phase A component is heavily

affected, which is consistent with the nature of the simulated fault (A-G). This disturbance is directly reflected in the loss function curve, whose amplitude increases markedly during the fault periods, reaching a value much higher than that observed during normal operation, which is zero. In parallel with this increase in loss, the *Fault detect line 1* curve rises from 0 to 1 precisely during the two intervals when the fault is active, before returning to 0 when the system returns to normal operation. This curve represents our detection system's response to the presence of a short-circuit fault on the line. This confirms that the LSTM autoencoder model detects anomalies in real time while adhering to the fault occurrence timing.

4.2 Real-time fault detection in two transmission lines

In a meshed power network, short-circuit faults can occur simultaneously on multiple lines due to severe disturbances or unstable operating conditions. These faults can influence the overall behavior of the network and affect other lines not directly impacted, making real-time detection crucial to limit their propagation, protect equipment, and ensure service continuity. To assess the LSTM model's ability to detect such multi-line faults, a simulation was carried out on the network with two successive events: a single-phase A-G fault on line 1 between 0.5 s and 1 s, followed by a three-phase ABC fault on line 6 between 2 s and 2.5 s. Figure 8 shows the Simulink scope output obtained during this simulation.

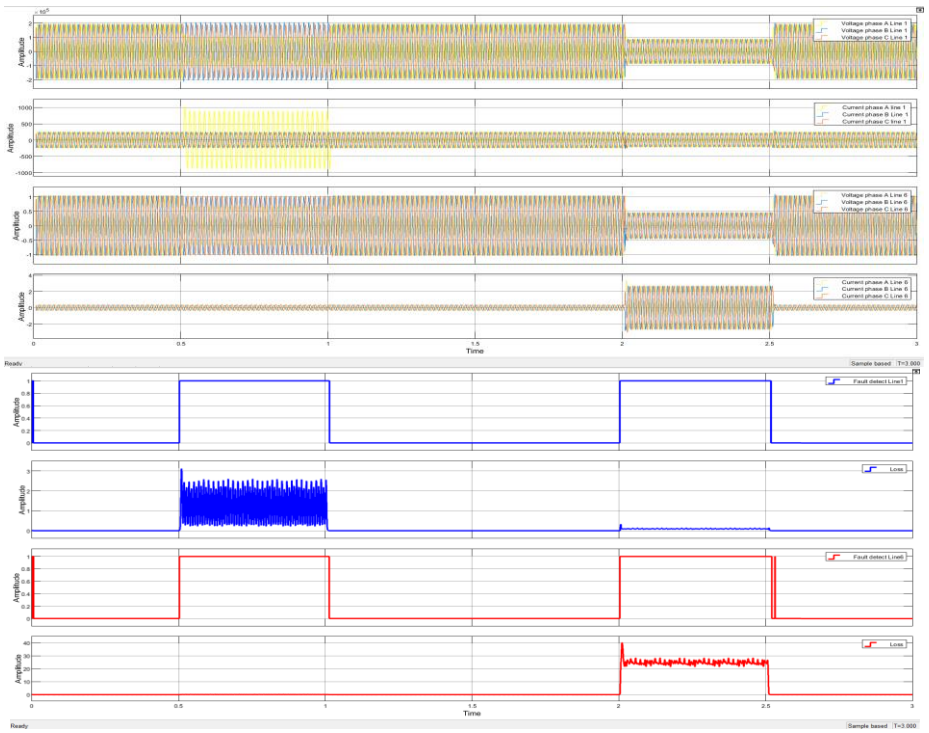

Fig. 8. Scope output for the real-time detection of an A-G fault on line 1 and an ABC fault on line 6

4.2.1 Result analysis

The analysis of the voltage and current signals on lines 1 and 6 highlights clear disturbances during the fault intervals. Variations in the electrical quantities are clearly observed at the

moments of the faults, reflecting the presence of a single-phase A-G short-circuit on line 1 (between 0.5 s and 1 s) and a three-phase ABC fault on line 6 (between 2 s and 2.5 s). However, what is particularly noteworthy is that line 6, although not directly affected by the first fault, also shows a response. Specifically, the detection curve for line 6 (in red) briefly rises to 1 during the same time interval (0.5 s to 1 s), and while the loss function remains very low, it experiences a slight disturbance. Similarly, the detection curve for line 1 (in blue) rises to 1 during the time interval (2 s to 2.5 s), despite an almost negligible loss function. These secondary losses can be explained by the propagation of electrical disturbances through the network, which slightly affect the signals of other lines not directly involved. In an interconnected network, a fault on one line can cause imbalances or circulating currents in other branches, which the model detects as minor anomalies.

4.3 Real-time fault detection in three transmission lines

When multiple lines in a power network are simultaneously subjected to short-circuit faults, the dynamic interactions between these lines become more complex, making detection even more challenging. It is therefore essential to have monitoring mechanisms capable of tracking, in real time, the evolution of electrical signals across several branches of the network. To assess this capability, three faults were simulated in the power network: a double line-to-ground fault of type AB-G was introduced on line 1 between 2.5 s and 3 s, a single line-to-ground fault of type B-G was injected on line 2 between 1.5 s and 2 s, and a double line fault of type BC was applied on line 6 between 0.5 s and 1 s. Figure 9 illustrates the Simulink scope output obtained during this simulation.

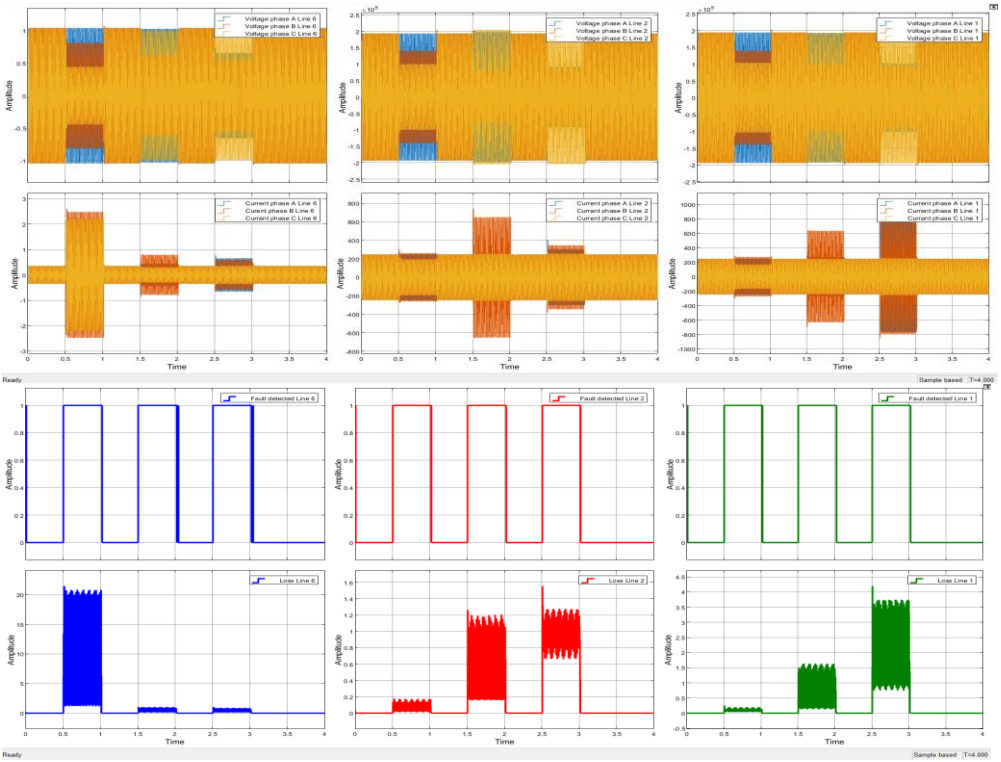

Fig. 9. Scope output for the real-time detection of an AB-G fault on line 1, a B-G fault on line 2, and a BC fault on line 6.

4.3.1 Result analysis

The analysis of the voltage and current signals on lines 1, 2, and 6 highlights the presence of three different types of faults occurring over distinct time intervals. The signals clearly show significant disturbances in currents and voltages during the fault intervals, reflecting the direct impact of each fault on its respective line. The LSTM autoencoder model successfully detected these faults in real time, as evidenced by the detection curves and corresponding loss function values. In addition, an inter-line influence is observed. The BC fault on line 6 caused a moderate effect on line 2 (slightly elevated loss function) but a very minor effect on line 1. This partial propagation can be explained by the topological proximity between lines 6 and 2 in the network. Conversely, the B-G fault on line 2 strongly influenced line 1, as indicated by a significantly high loss function, while the impact on line 6 remained limited. Finally, the AB-G fault on line 1 had a strong impact on line 2 (high loss detected) but only a very small effect on line 6. This propagation can be explained by the fact that line 2 is in close proximity to line 1. This analysis highlights that the closer the lines are in the network, the more a disturbance on one line can affect the others. Furthermore, the nature of the fault (single-phase, two-phase, with or without ground) plays an important role in the amplitude of the detected losses. Faults involving ground, particularly AB-G and B-G types, tend to generate a stronger response due to the asymmetry introduced into the system, compared with a simple two-phase fault such as BC.

5 Conclusion

This paper has presented an effective method for real-time short-circuit fault detection in meshed power networks, leveraging the capabilities of LSTM autoencoders to model the network's normal behavior and identify any significant anomalies. Unlike classical approaches and offline models, our system processes data continuously and instantaneously, enabling fault detection at the exact moment of occurrence, including cases where multiple lines are affected simultaneously. Simulation results on the IEEE 9-bus network confirm the model's ability to detect both simple and hybrid faults while highlighting inter-line influences caused by the propagation of electrical disturbances. This ability to account for the indirect impact of faults on other parts of the network enhances diagnostic reliability. Furthermore, the achieved accuracy and robustness against topology changes and varying operating conditions demonstrate that this approach is particularly well suited to the needs of intelligent protection systems in modern power networks. Ultimately, its integration could significantly improve responsiveness, reduce downtime, and limit equipment damage related to electrical incidents.

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