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ENHANCING FAULT PREDICTION IN ELECTRIC POWER DISTRIBUTION USING WAVELET-LSTM INTEGRATION DURING THE COVID-19 PANDEMIC

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Abstract: The duty of an electric power distribution company is to ensure a consistent and reliable flow of electricity to its customers. Interruptions in the electrical system can negatively impact the grid's reliability metrics and its overall efficiency. Therefore, the ability to predict outages is essential to minimize downtime and quickly restore service. This study examines the occurrence of system failures throughout the initial year of the pandemic in Brazil (2020) and assesses the potential of utilizing time series prediction models for outage forecasting. The research evaluates the long short-term memory (LSTM) model to produce predictive insights that could guide electric utilities in scheduling maintenance crews more effectively. Incorporating the wavelet transform with the LSTM model appears to enhance the prediction accuracy, making it a promising combination for this research. Comparative analyses indicate that this method yields superior prediction accuracy and demonstrates reliability through statistical validation.

Keywords: *electric power distribution, outage prediction, long short-term memory (LSTM), time series analysis, wavelet-LSTM integration.*

1. INTRODUCTION

Electric power grids must operate reliably regardless of weather conditions to ensure stable electricity supply to consumers. To maintain operational stability, it's crucial to simulate and evaluate the performance of the grid's equipment to identify any disturbances [1,2]. These disturbances can lead to power supply issues, voltage variations, and increased fault risks due to factors like high surface conductivity or ground contact by conductors, ultimately degrading power quality [3].

Time series forecasting is a valuable tool for predicting potential failures, aiding maintenance decision-making processes in utilities [4]. Notably, failure rates correlate strongly with weather conditions; for example, failures are more likely during rainy seasons [5]. Studying these variations through time series analysis is vital.

The application of wavelet transforms, which are effective in managing high nonlinearity in time series without significant data loss, supports maintaining essential signal characteristics even when filtering high frequencies that could indicate potential failures [6,7]. Combining wavelet transforms with deep learning models like Long Short-Term Memory (LSTM) — known for addressing the vanishing gradient problem and enhancing time series forecasting — creates a robust hybrid approach [8-12].

This study leverages wavelet LSTM, a novel method that fuses wavelet transforms with LSTM, to analyze alarm data from a recloser in Santa Catarina, Brazil [13-16]. This hybrid model demonstrates improved prediction stability and accuracy over traditional LSTM, providing valuable insights into fault occurrences in electrical grids with bare cables, where contamination and foreign material contact can cause disruptions.

The paper progresses with a literature review and data methodology, followed by an exposition of the proposed wavelet LSTM approach, results analysis, and concludes with a discussion on the implications and future directions of this research.

II. RELATED WORKS

In electrical distribution systems, faults are defined as anomalies disrupting equipment operation within the power grid [17]. Faults are categorized into transient—short-lived disturbances resolved by protective devices—and permanent, which persist until defective components are replaced [18].

Fault diagnosis tools assess the location, size, duration, and impact of these disturbances [19]. Advanced methods like Bayesian networks [20], fuzzy logic [21], and Kalman filters [22] are employed alongside AI-driven models to enhance fault identification capabilities, which have become increasingly vital in the electrical power sector [23]. Particularly, deep learning models such as LSTM are favored for their efficiency in fault detection, despite requiring significant computational resources due to their complexity [24-27].

Image processing techniques using CNN models, such as YOLO and Faster R-CNN, further aid in identifying faulty components by recognizing patterns in images of damaged equipment [28-35]. These models, especially newer versions like YOLOv4, demonstrate high accuracy in fault identification within power grids [32-40].

Environmental factors, like tree branches contacting uninsulated conductors, commonly cause faults in rural grids [41]. Measures like tree pruning near power lines are preventive actions taken to mitigate such incidents [42]. Additionally, environmental exposure can lead contaminants like dust and salt to accumulate on insulators, increasing leakage currents and the likelihood of faults, particularly under high humidity conditions [43-46].

Time series forecasting is employed to prepare maintenance teams for potential faults by analyzing historical data variations [47,48]. While forecasting multiple steps ahead poses challenges due to error accumulation, ensemble learning models are noted for their robust performance in multi-step forecasting with less computational demand, making them suitable for predicting power system failures [51-58].

LSTM models are particularly effective in handling chaotic time series in power systems due to their capability to remember long-term dependencies, essential for accurate prediction [59-62]. The integration of LSTM with attention mechanisms and modifications for specific applications like wind power forecasting further illustrates its adaptability and effectiveness in the sector [60-62].

Table 1. Example of Alarms Registered During the Considered Period

Day	Time	Failure Record
7 January 2020	11:10:45	Current Phase B
7 January 2020	11:10:55	Current Phase A
7 January 2020	17:11:30	Current Phase C

25 January 2020	14:00:20	Recloser Communication Failure
07 April 2020	10:05:20	Relay 50/51 (Neutral)
02 June 2020	17:25:50	Current Phase A
01 July 2020	14:12:00	Phase Voltage C
28 August 2020	10:01:00	Neutral Protection
28 August 2020	12:00:00	Current Phase C
12 September 2020	03:07:10	Current Phase A
30 December 2020	14:00:00	Relay 50/51 (Phase A)

This table shows the type and timing of alarms that occurred during the specified period, demonstrating the frequency and nature of electrical faults recorded by the utility company.

The alarms summarized in Table 1 detail the day, time, and cause of each recorded failure. The complete dataset, which includes all documented alarms, is accessible at GitHub (accessed on October 21, 2021).

Failures in electrical systems typically manifest in a nonlinear fashion, making it challenging to predict their exact occurrence. Nevertheless, it is feasible to determine periods throughout the year that are more susceptible to a higher incidence of failures. This paper reviews the fault history for the year 2020—from January 1 to December 31—a leap year with 366 days, focusing on the distribution networks in the Lages region of Brazil, utilizing data provided by Centrais Elétricas de Santa Catarina (CELESC).

Figure 1 in the document illustrates the daily sum of alarms related to faults during this period, offering a visual representation of the frequency and distribution of failures over the year.

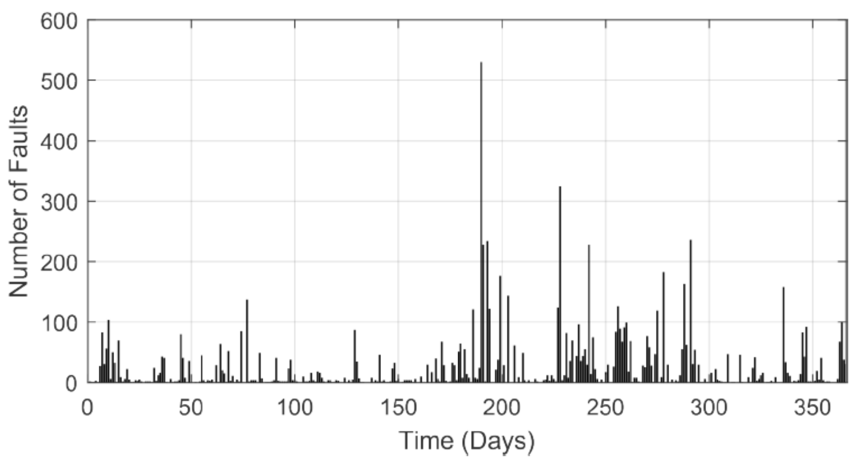

Figure 1. Failures registered in the power grid in 2020 (Lages region).

3. Wavelet LSTM

The wavelet LSTM method merges wavelet transform with long short-term memory (LSTM), enhancing fault diagnosis in electrical machines and rolling bearings, as demonstrated by Sabir et al. [64] and Tan et al. [66]. Its use extends to time series forecasting across various sectors including the Internet of Things [67-69], industrial applications [70-72], and sustainability [73].

The application process of the wavelet LSTM model involves several steps, illustrated in Figure 2. Initially, the time series data undergoes noise and nonlinearity reduction via a wavelet filter (Step A). This involves decomposing (Step B) and then reconstructing (Step C) the signal. The denoised signal is then normalized (Step D), taking into account the variance in the number of faults recorded during the period under review. Finally, the LSTM model predicts future trends based on this processed data (Step E). This sequential method enables precise and effective forecasting of time series data.

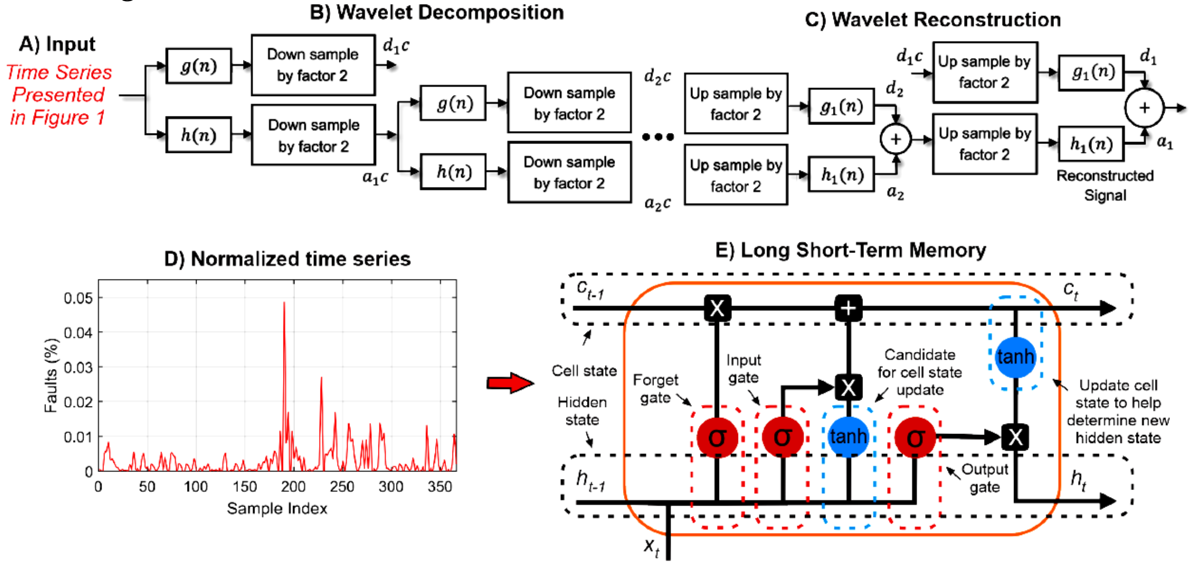

Figure 2. Structure of the wavelet long short-term memory model.

To implement the wavelet transform, the signal initially underwent decomposition via the wavelet packet transform (WPT) method, which is designed to capture the energy coefficient of the signal, analyzing both high and low frequency components of the spectrum. This decomposition process can be represented by

$$W_{\Psi,x}(A,B) = \frac{1}{\sqrt{A}} \int_{-\infty}^{+\infty} x(t)\Psi * \left(\frac{t-B}{A}\right) dt,\ A \neq 0 \tag{1}$$

where $x(t)$ is the signal to be decomposed, *Y* represents the time-based function (mother wavelet), and *A* and *B* are the scale and displacement parameters, respectively [74]. Upon discretization, the high-pass filter $g(n)$ is defined as

$$g(n) = h(2N - 1 - n). \tag{2}$$

where $h(n)$ is the low-pass filter. Correspondingly, the mother wavelet and the scaling function *F* are defined by

$$\Psi(n) = \sum_{i=0}^{N-1} g(i)\Phi(2n - i), \tag{3}$$

$$\Phi(n) = \sum_{i=0}^{N-1} h(i)\Phi(2n - i). \tag{4}$$

The Wavelet Packet Transform (WPT) continues to decompose the signal at each iteration using the coefficients from prior iterations, resulting in the total number of coefficients being dependent on the number of iterations performed. Each coefficient in the wavelet packet is characterized by its specific frequency level, allowing for a comprehensive decomposition that includes both high and low frequency components of the signal. This method utilizes a tree structure, derived from the approximation decomposition coefficients, to ascertain an optimal binary value. An illustration of this tree structure used for wavelet decomposition is showcased in Figure 3.

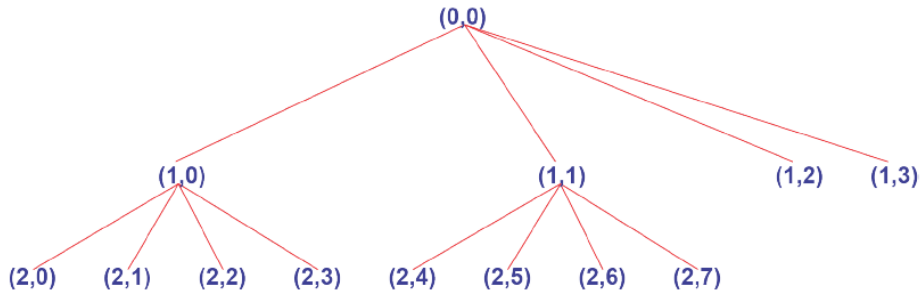

Figure 3. Tree decomposition.

In the optimized structure, certain paths, specifically paths 1, 2, and 1, 3, are excluded, leading to a more streamlined decomposition process. Following the optimized wavelet packet decomposition, the signal is reconstructed based on the selected nodes from the binary wavelet packet tree. This reconstructed filtered signal then serves as the basis for generating a time series, which is subsequently utilized for evaluating LSTM forecasts.

LSTM (Long Short-Term Memory) is a type of recurrent neural network characterized by its feedback connections, enabling the model to retain information from distant data points. To perform time series forecasting, the LSTM model begins its predictions from *D* samples, leveraging its memory capability to enhance forecast accuracy.

4. Analysis of Results

The initial evaluation focused on analyzing the time series forecasting performance in relation to the distribution of data between training and testing phases within the neural network. This aspect is crucial as it helps determine the minimal dataset size required effectively to train the model. The optimal outcomes from this analysis are emphasized in bold within this section.

The findings are summarized in Table 2, which illustrates varying training ratios ranging from 50% to 90%. The complementary percentage to each training ratio was allocated for testing purposes, with no separate validation set involved in this particular assessment.

Using an 80% training and 20% testing data split yielded the most favorable results, achieving the best RMSE (Root Mean Square Error) and R^2 (coefficient of determination) values. Consequently, this ratio was adopted for subsequent analyses. As illustrated in Figure 4, predicting the data presented significant challenges due to the nonlinear nature of the time series. This complexity was particularly evident in instances where multiple failures occurred within a brief timeframe.

Table 2. Evaluating the influence of the training and testing relationship.

Train/Test	RMSE	MAE	R^2	Time (s)
50/50	8.02×10^{-3}	3.03×10^{-3}	0.1516	**17.21**
60/40	6.24×10^{-3}	7.47×10^{-4}	**0.1681**	18.53
70/30	4.73×10^{-3}	3.59×10^{-4}	0.0325	18.64
80/20	$\mathbf{3.60 \times 10^{-3}}$	1.18×10^{-3}	0.2779	20.47
90/10	4.29×10^{-3}	$\mathbf{5.49 \times 10^{-5}}$	0.0884	19.68

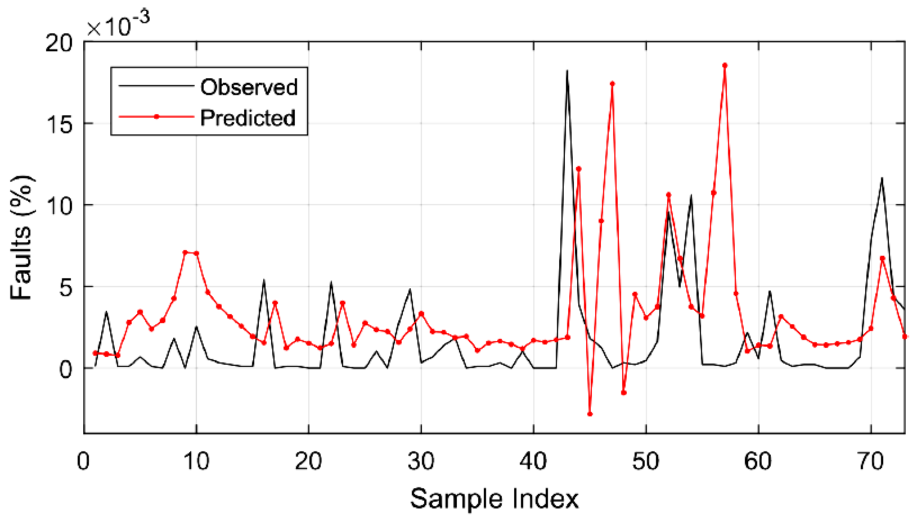

Figure 4. Preliminary analysis of fault prediction capability.

5. Conclusions

Predicting faults within an electrical distribution system is crucial for maintaining reliable power grid operations. By analyzing time series data, it is possible to identify periods with increased failure rates, which can inform more effective mitigation strategies. Time series forecasting allows electric utilities to anticipate faults, enabling them to develop proactive measures to address potential issues. The task of predicting failures is challenging due to significant seasonal fluctuations in failure rates, particularly during the rainy seasons. Traditional forecasting models proved inadequate for handling these variations, necessitating the development of a hybrid model to better address the complexities involved. The wavelet LSTM model outperformed the standard LSTM in all conducted analyses, demonstrating superior results in statistical assessments and proving to be well-suited for this study. This model provides reliable failure prediction indicators that can assist in the efficient organization of maintenance crews, thereby reducing the time to respond to critical failures. The basic LSTM model, while potent for chaotic time series, struggled without additional modifications due to the sharp fluctuations in failure data. Incorporating a wavelet filter into the LSTM model enabled effective smoothing of the time series, enhancing the prediction accuracy beyond that of other advanced methods like ensemble learning, GMDH, and ANFIS. Future research should focus on differentiating between types of failures, such as those caused by direct contact with the grid versus leakage currents. Detailed analysis of the most frequent failure types and strategies to prevent them presents a promising avenue for further investigation.

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