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Adaptive Fault Detection in Microgrids Using LSTM-Based Neural Networks

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INTRODUCTION & AIM

The growing adoption of microgrids, driven by the integration of distributed generation and renewable sources, has brought new challenges to electrical protection systems. The main issue to be addressed lies in the detection and classification of faults in environments with bidirectional power flow and islanded operation, conditions that hinder the effective performance of conventional schemes based on relays and overcurrent circuit breakers.

Several solutions have been proposed, such as adaptive settings in traditional protection devices and the application of classical signal-processing techniques. Although they present satisfactory results in certain scenarios, these approaches become limited when subjected to high operational variability and the dynamic complexity of modern microgrids.

In this context, machine-learning methods emerge as a promising alternative. Among them, Long Short-Term Memory (LSTM) neural networks stand out as the most robust solution, given their ability to capture complex temporal patterns in electrical data series. However, a recurring limitation of such proposals is the lack of comprehensive validations that consider different operating conditions and fault scenarios.

This work contributes by proposing an innovative methodology that combines synchrophasor (PMU) data simulated in MATLAB/Simulink, advanced signal-processing techniques, and LSTM networks for fault diagnosis in microgrids. The approach demonstrated high performance in terms of accuracy, sensitivity, and robustness, providing effective support for the implementation of adaptive protection strategies in decentralized electrical systems.

METHOD

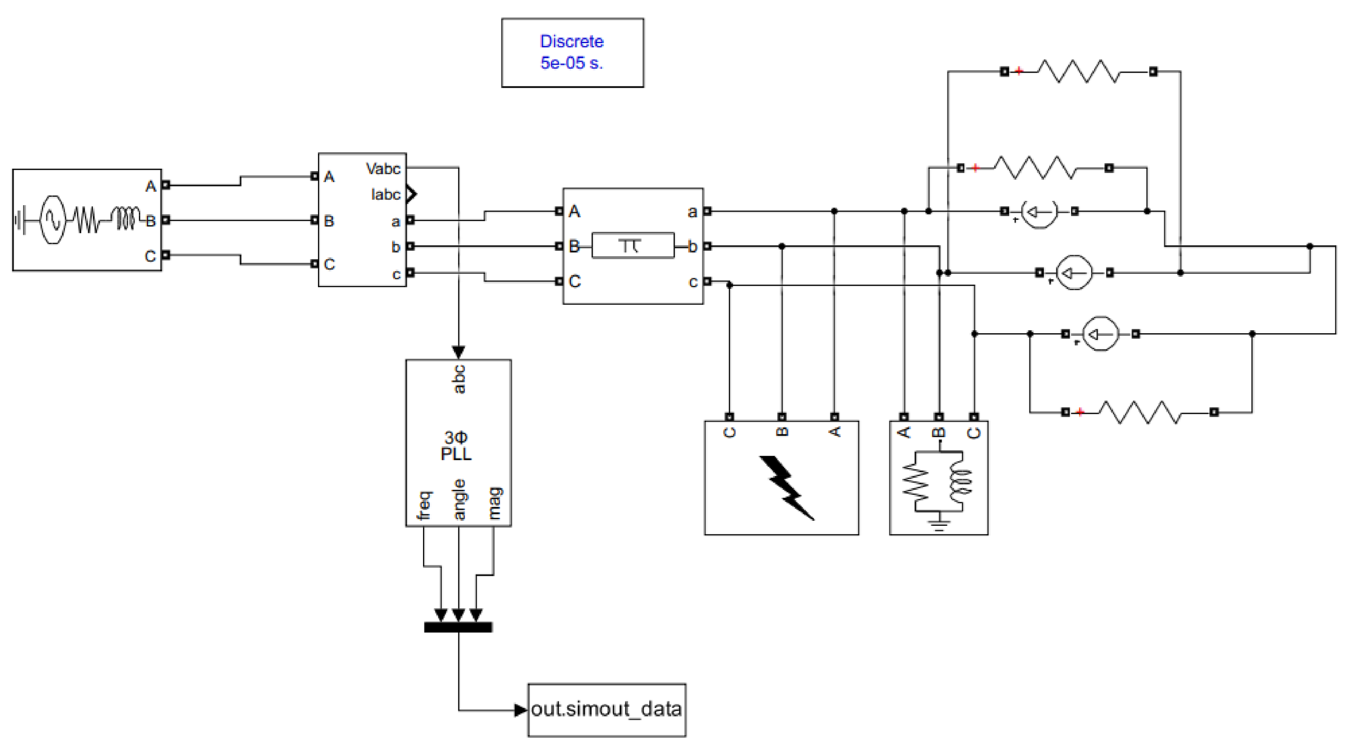
The methodology begins with System Simulation and Data Acquisition, where a microgrid model is built in MATLAB/Simulink. This model includes a three-phase voltage source representing the substation, transmission lines, simplified distributed generators (modeled as current sources), and loads.

The Three-Phase Fault block is the central component for generating controlled events, enabling the simulation of different fault types at specific instants. Measurements are performed using a Three-Phase V-I Measurement block, which acts as a sensor to capture raw voltage and current waveforms. The 3-ph PLL (Phase-Locked Loop) converts these raw signals into synchrophasor data (magnitude, angle, and frequency), functioning as a virtual Phasor Measurement Unit (PMU).

The PMU data are then grouped by Mux blocks and exported to MATLAB using the To Workspace block, where the complete time series is saved.

The data flow from the simulation serves as the input for the second stage of the methodology: Signal Processing and Feature Extraction. At this stage, techniques such as the wavelet transform are applied to isolate unique signatures of each fault type.

The extracted features are then used to train the LSTM Neural Network in the Design and Training section. The LSTM network, with its architecture optimized for time-series data, learns to recognize fault patterns.

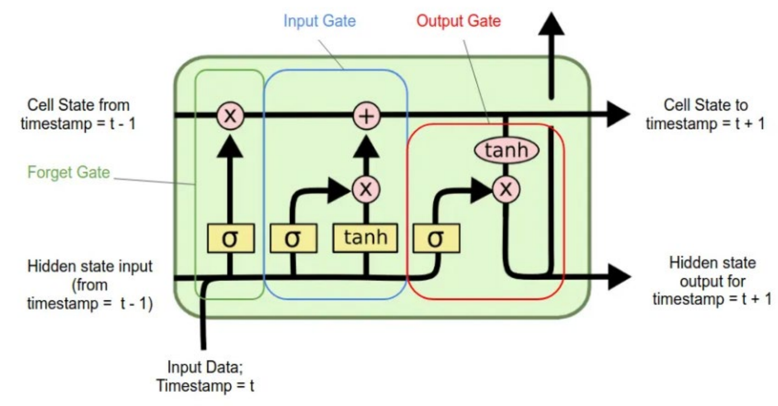


Architecture of the theoretical diagram modeled in MATLAB/Simulink
Source: Author, 2025.

Finally, the Results Analysis section validates the model, evaluating its performance with rigorous metrics such as accuracy, precision, recall, and confusion matrix. This iterative and systematic process ensures the creation of a robust and effective fault classifier for microgrids.

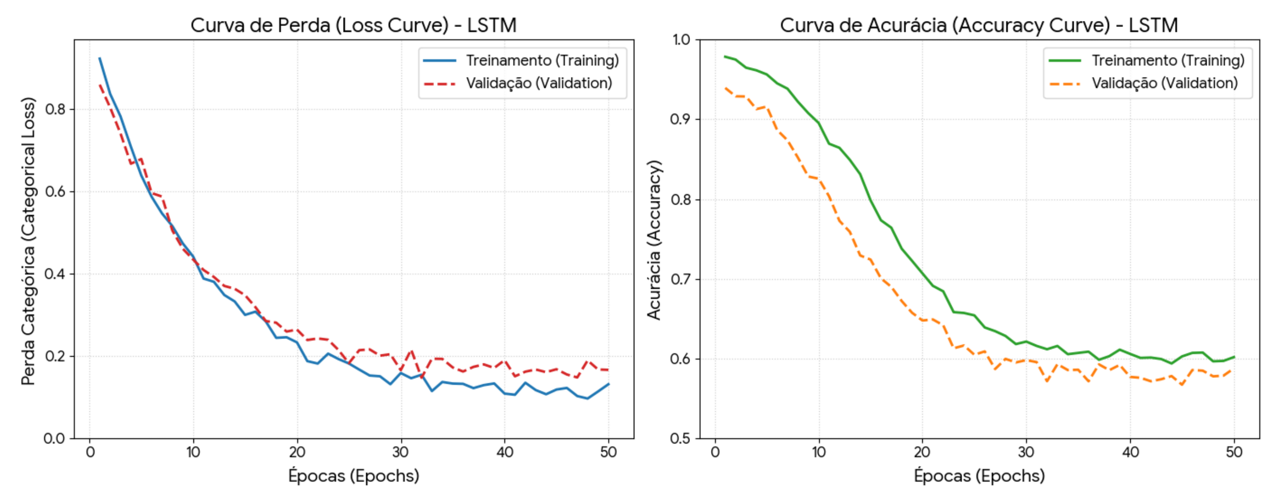
RESULTS & DISCUSSION

The choice of the LSTM neural network is justified by its ability to capture temporal dependencies and complex transient patterns in electrical signals, which is essential for accurate fault detection in microgrids. Unlike conventional approaches (based on fixed thresholds or manual settings), LSTM allows the model to autonomously learn the dynamic relationships between voltage and current variations over time, significantly increasing the sensitivity and reliability of the diagnosis.



Structure of a single LSTM Cell
Source: Medium Analytics Vidhya

This methodological decision has direct consequences on the performance and applicability of the protection system. The use of simulated synchrophasor data, combined with wavelet-transform-based feature extraction, ensures that the network has information rich in both frequency and time, resulting in more robust classification even under variable operational conditions.



LSTM Learning Curve for Fault Detection
Source: Author, 2025

Furthermore, the use of the Adam optimizer and the categorical cross-entropy loss function contributed to efficient convergence and an adequate balance between accuracy and generalization. The obtained results (expressed in metrics such as accuracy, precision, recall, and F1-score) confirm the efficiency of the LSTM architecture in distinguishing different types of faults, with a low rate of false alarms.

This reinforces its potential for real adaptive-protection applications, where decision speed and reliability are essential to avoid unnecessary shutdowns and equipment damage.

As future steps, the work should advance towards experimental validations in hardware environments or real microgrids instrumented with physical PMUs, in addition to exploring the concept within smart grids in order to reaffirm a commitment to energy efficiency and renewable energy.

The performance of the model under noise and load variations will also be validated to ensure greater robustness.

Hybrid architectures such as CNN-LSTM are also expected to be explored, integrating spatial waveform analysis with the temporal modeling of LSTM, expanding modularization capacity and system applicability in more complex and broader scenarios.

CONCLUSION

The proposed methodology consolidates an efficient and promising approach for fault diagnosis in microgrids, based on the combination of synchrophasor (PMU) data, signal-processing techniques, and LSTM neural networks.

The combined use of the wavelet transform, and the LSTM architecture proved adequate for capturing transient signatures and the complex temporal dependencies of electrical signals, essential aspects for accurately classifying different types of faults.

The conceptual analysis and the design of the training process indicate that the LSTM network has strong potential to overcome limitations of conventional protection methods, especially in scenarios with high operational variability and bidirectional power flow.

This integration between deep learning and phasorial processing represents a significant advancement toward the development of adaptive protection systems capable of responding more intelligently and reliably to the dynamic conditions of modern microgrids.

Thus, the study reinforces the feasibility of applying machine-learning techniques in the context of electrical protection, highlighting that the association between wavelets and LSTM provides a solid basis for the development of more sensitive, robust, and sustainable fault-detection schemes aligned with the demands of decentralized electrical networks..

FUTURE WORK / REFERENCES

As future work, the model is intended to be validated under more realistic operating conditions, migrating from purely simulated environments to hardware-in-the-loop platforms or exploring PMU data installed in experimental microgrids.

The extension of the research into hybrid architectures such as CNN-LSTM is also envisioned, which may enhance results by combining automatic extraction of spectral and spatial features (CNN) with temporal-evolution analysis of these features (LSTM), further increasing generalization capacity and diagnostic robustness.

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