Voltage-Based Islanding Control for Grid-Connected RES for Grid Stability Using Deep Learning

Remon Das[1], Akash Debnath[2], Ushna Das[3]
[1]Renewable Infrastructure, Dominion Energy, VA, USA
[2]Operational Planning, Dominion Energy, VA, USA
[3]Chittagong University of Engineering and Technology, Chattorgram, Bangladesh
remondas4@gmail.com, akashaust11@gmail.com, ushnadas51@gmail.com

***Abstract*—The increasing integration of Renewable Energy Sources (RES) such as photovoltaic power plants and wind turbines creates difficulties when it comes to maintaining grid stability as well as fulfilling the Low Voltage Ride Through (LVRT) criteria. Existing conventional methods for protection fail to possess the necessary flexibility in dealing with different kinds of fault situations. This study proposes a deep learning-based approach for voltage-controlled islanding control of grid-connected RES using Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and hybrid CNN-LSTM network structures. The training data was developed in a MATLAB/Simulink environment for creating different cases of symmetrical and asymmetrical fault occurrences. All models are trained to recognize the fault occurrence and maintain voltage stability when there are grid failures. Based on the results, all three models can successfully conduct voltage-controlled islanding control, but the best fault detection accuracy of 99.97% is achieved by the CNN-LSTM model.**

***Index Terms*—Renewable energy, smart grids, CNN, LSTM, CNN-LSTM, LVRT**

I. Introduction

While crucial for reducing carbon emissions, adding large amounts of renewable energy sources (RES) like solar and wind to the power grid creates new problems for its stability and strength. Unlike traditional power plants, RES output is variable and not always predictable. This can cause unwanted voltage changes, power flow swings, and situations where parts of the grid become disconnected (islanding). These events threaten the reliable operation of grid-connected systems. Therefore, to ensure that high levels of RES do not harm the main grid's performance, two things are critical: maintaining steady voltage and developing smart controls that can adaptively manage islanding events. Effective monitoring and intelligent control of voltage in RES-heavy networks are thus essential. This secures the grid's resilience and supports the ongoing shift to sustainable energy [1], [2]. For grid stability and resilience, the growing advancement of Renewable Energy Sources (RES) into modern power systems offers numerous advantages and complications. The grid is now much more susceptible to disruptions like faults, voltage sags, and unplanned islanding due to the rising percentage of decentralized energy from photovoltaic (PV), wind and other renewable energy sources [3].

To mitigate damage, renewable energy units had to disconnect from the grid during fault conditions under earlier grid code frameworks. This approach may have an adverse effect on grid strength and decreased energy availability to loads beyond the fault zone as renewable integration expands [4]. To increase power system dependability and operational resilience, a few nations, including Germany, Italy, and Japan, have updated their grid code standards. These upgraded guidelines require renewable energy installations to stay connected to the grid during network fault-induced power drops [5]. Photovoltaic power, like wind energy, affects grid dynamics and steady-state performance as it grows. PV systems must have good LVRT control to withstand voltage sags without disconnecting from the grid. Due to their inability to respond to unforeseen or unknown disturbances, standard LVRT control techniques frequently have low prediction accuracy under unexpected fault circumstances [6], [7]. Grid faults, such as those arising from transmission line disturbances or equipment failures, can induce significant voltage deviations, thereby threatening overall system stability and resilience [8], [9].

Machine learning and deep learning techniques have been extensively applied to power system monitoring, fault diagnosis, and voltage stability assessment, particularly with the increasing penetration of renewable energy sources. Traditional approaches, including artificial neural networks, decision trees, and support vector machines, have been used to analyze voltage disturbances and detect abnormal operating conditions [11], [12]. Most recently, hybrid deep learning architectures have demonstrated superior capability in capturing both spatial and temporal characteristics of power system signals, making them effective for voltage-based islanding detection and resilient grid operation [13]. Several studies have reported promising results using CNN–recurrent network combinations. A CNN–GRU framework achieved a fault classification accuracy of 93.92%, outperforming CNN–LSTM and CNN–RNN models [10], while a CNN–LSTM-based intrusion detection system for smart grids attained a detection accuracy of 99.70%, highlighting its effectiveness in cybersecurity applications despite higher computational complexity [3]. Similarly, a CNN–LSTM emergency control coordination method for voltage stability assessment achieved an average prediction accuracy of 99.247%, demonstrating strong potential for real-

TABLE I
SUMMARY OF DEEP LEARNING-BASED POWER SYSTEM APPLICATIONS

SL.	Model/Reference	Key Feature	Application Domain	Accuracy
1	CNN–GRU, CNN–LSTM, CNN–RNN [10]	Real-Time Fault Detection and Remediation	Enhancing Power Grid Resilience	93.92%, 93.05%, 92.85%
2	CNN–LSTM [3]	Intrusion Detection	Improving the Cybersecurity of Smart Grids	99.70%
3	CNN–LSTM [4]	ODOP-Based Emergency Control Strategy	Voltage Stability Assessment Under Large Disturbances	99.247%
4	RNN–LSTM [6]	High-Impedance Fault Detection	Solar PV-Integrated Power Systems	91.21%
5	2D-CNN [7]	Continuous Wavelet Transform (CWT)	Transmission Line Fault Classification and Detection	99.9074%
6	Double CNN [8]	1D Convolutional Autoencoder + 1D CNN	Temporary Fault Identification in Power Distribution Systems	93.8%

time decision support in modern power systems [4].

Deep learning has also been widely adopted for fault detection and classification in renewable-integrated and distribution networks. An LSTM-based model for high-impedance fault detection in a solar PV-integrated IEEE 13-bus system achieved an overall classification accuracy of 91.21% and a fault detection rate of 92.42% [6]. For transmission line protection, a 2D-CNN framework utilizing continuous wavelet transform scalograms successfully classified twelve fault categories with an accuracy of 99.9074% [7]. Likewise, a double convolutional neural network (DCNN) approach combining convolutional autoencoders and CNN-based classification attained 93.8% accuracy in transient fault identification within power distribution systems [8]. These studies collectively demonstrate the effectiveness of deep learning models in improving fault diagnosis, stability assessment, and operational reliability across modern power networks.

Despite major progress in deep learning, most fault diagnosis research still relies on isolated voltage or current measurements and doesn't often factor in grid-code rules like Low Voltage Ride Through (LVRT). This limits how adaptable the methods are for real-world issues [14], [15]. To address this, our study suggests a voltage-based hybrid CNN–LSTM framework for managing islanding in grid-connected renewable energy systems. In this setup, the CNN layers pull out important fault features from LVRT-encoded voltage data, while the LSTM layers focus on the changing dynamics over time. This approach is smart because it builds grid-code compliance right into the learning process. It skips the need for detailed manual feature creation, making islanding control faster, more adaptable, and dependable. Plus, it uses precise PMU-based voltage readings to improve overall grid stability in renewable power networks [16], [17].

II. METHODOLOGICAL FRAMEWORK

A. Data Collection and Preprocessing

A renewable power generation process model was designed in MATLAB/Simulink to simulate a realistic renewable energy integration scenario and generate voltage fault and LVRT data under different operating modes. The modeled system consists of a 25 kV, 60 Hz renewable energy power plant connected to the power grid through a 25/132 kV step-up transformer. A 20 MVA renewable energy source (RES) is integrated via a 13.8 kV transmission line and a 132/13.8 kV transformer, while both the grid and RES are interconnected through a 0.575/13.8 kV step-up transformer to supply 30 MVA loads at the 13.8 kV level. Using this setup, a total of 500 fault scenarios were generated, each containing approximately 410,000 data points composed of three-phase voltage signals (Va, Vb, Vc) and LVRT threshold values. The raw datasets were subsequently segmented using a sliding window approach with a window length of T = 100 and step size of 1, producing an input tensor of size (N, 100, 4).

If any phase voltage was below the LVRT threshold value, the corresponding windows were marked as "islanded" mode, and all other windows were classified as "connected". In order to decrease memory requirements, only 5% of all possible windows for each file were randomly chosen. After that, train/validation/test splitting by stratified sampling was performed in order to prevent data leakage as shown in fig. 1. As normalization and class weighting methods were used, MinMax scaler and calculated class weights respectively. The number of samples for testing was set at 5,943 connected windows and 206 islanded windows.

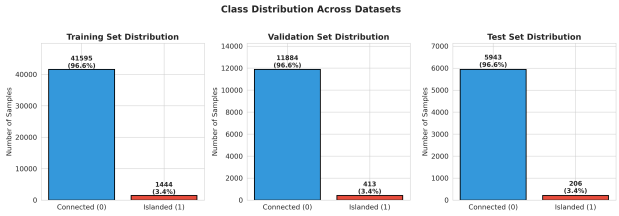

Fig. 1. Class Distribution Across Datasets

B. Proposed Architecture for RES Islanding Control

The proposed islanding controller combines one-dimensional convolutional layers for spatial modelling of features and long short-term memory (LSTM) layers for the temporal modeling. The study focuses on the fact that the convolutional layers are used to capture the local

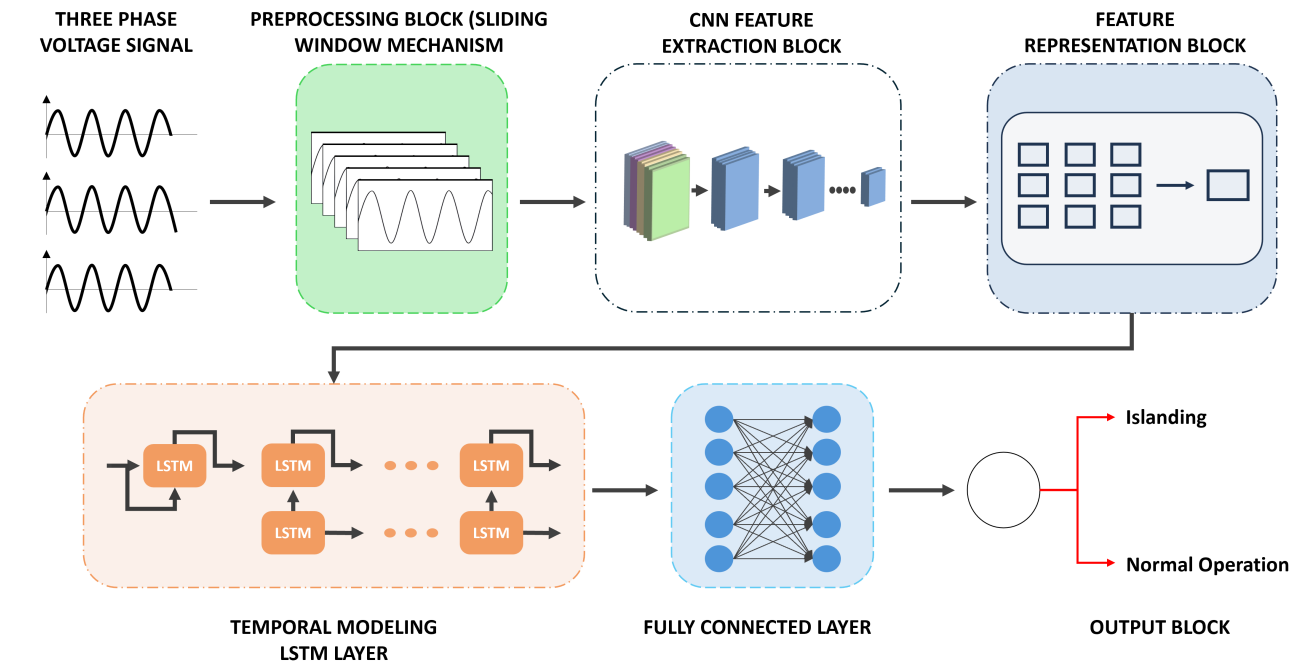

Fig. 2. Overall Architecture for Proposed Model

patterns in the voltage waveforms, while the LSTM layers are used to model the temporal dependencies within the sliding window. The network input consists of a sequence of 100 samples that consists of the three line voltages and the LVRT threshold. Two convolutional blocks with batch normalization, rectified-linear, max-pooling and dropout are used to create compact feature maps from the four-dimensional input. These feature maps are then passed into a stacked LSTM block. The first LSTM has 128 units and outputs a sequence to maintain a temporal context and the second LSTM has 64 units and outputs a single hidden state. The resulting temporal representation goes through two fully connected layers (64 and 32 neurons), including L2 regularization and dropout, before going through a final sigmoid unit, the output of the probability of the islanded class. Training is done using the Adam optimizer, an initial learning rate of $\mathbf{10^{-3}}$, gradient norm clipping of 1.0, binary cross-entropy loss, and class weights. Early stopping, reduced learning rate and model checkpoint callbacks are used to monitor the validation loss and accuracy. Figure 2 shows the overall architecture of the proposed CNN-LSTM model and the interaction between the preprocessing stage, the convolution model for feature extraction, temporal modeling and the final classification module.

1) Convolutional Neural Network: CNNs are proven as highly effective approachs in time series forecasting. The efficiency of CNN in the context of time series analysis can be attributed to its capability to identify valuable local structures in time. These tasks are accomplished by the use of 1D convolution kernels that traverse through the time sequence, carrying out convolution operations on the overlapping segments. An embedding vector, known as a token, is generated for each segment, which is characterized by critical elements in the underlying time series [18].

$$y_t = \sigma\left(\sum_{i=0}^{k-1}(w_i.x_{t+i} + b)\right) \tag{1}$$

where, y_t = Output of convolutional operation, W_i = 1D convolutional filter (kernel) of size K, x_{t+i} = input time series of length T, σ = Activation function, b = Bias of output map.

2) Long Short-Term Memory (LSTM): LSTM is an improved RNN architecture designed to capture long-term dependencies and overcome the vanishing gradient problem. It consists of a memory cell and three gates: forget, input, and output gates, which regulate information flow and update the cell state for sequential prediction tasks such as power and energy forecasting. Forget Gate f_t determines how much information from the previous cell state c_{t-1} should be retained.

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f) \tag{2}$$

Input Gate (i_t) controls the amount of new information added to the cell state and generates a candidate cell state $(\tilde{C}_t)$

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \tag{3}$$

$$\tilde{C}t = \tanh(W_c x_t + U_c ht - 1 + b_c) \tag{4}$$

Cell State Update c_t updates the memory cell by combining retained past information and newly generated information.

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{C}_t \tag{5}$$

Output Gate o_t determines which information from the updated cell state is passed to the hidden state.

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \tag{6}$$

$$h_t = o_t \odot \tanh(c_t) \tag{7}$$

where, σ denotes the activation function; $f_t, i_t, c_t, and o_t$ represent the forget, input, cell-state, and output gates, respectively; x_t is the input vector; $h_{t-1} and c_{t-1}$ are the previous hidden and cell states; $W, U, and b$ are trainable parameters.

III. Simulation Results

The proposed hybrid CNN-LSTM architecture, along with the standalone CNN and LSTM baselines, were trained on the pre-processed dataset. To ensure robust convergence and prevent overfitting, early stopping with a patience of 5 epochs and a dynamic learning rate scheduling mechanism were employed. The models were evaluated on a held-out test set comprising 6,149 windows, specifically partitioned into 5,943 connected and 206 islanded instances.

A. Comparative Performance Analysis

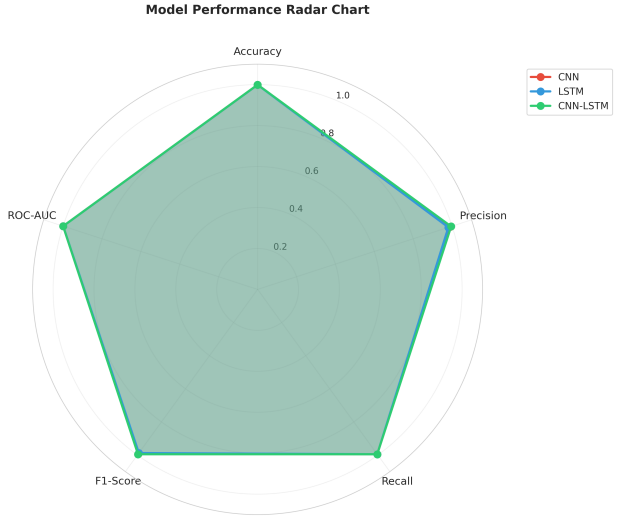

Fig. 3. Model Performance in Radar Chart

The experimental results, summarized in Table II and in Figure 3, demonstrate the superior performance of the hybrid framework. The CNN-LSTM model achieved the highest scores across all primary evaluation metrics, notably reaching an overall accuracy of 99.9675% and an F1-score of 0.995146.

While the standalone CNN baseline performed competitively, the LSTM-only model lagged behind significantly, particularly in terms of precision (0.980861) and PR-AUC (0.993775). This performance gap underscores the critical role of the convolutional layers; without convolutional feature extraction to capture high-level spatial and localized temporal patterns from the raw signal, the recurrent structure struggles to model long-term dependencies effectively.

TABLE II
Test Metrics for Each Evaluated Model

Metric	CNN	LSTM	CNN–LSTM
Accuracy	0.999512	0.999187	**0.999675**
Precision	0.990338	0.980861	**0.995146**
Recall	0.995146	0.995146	**0.995146**
F1-score	0.992736	0.987952	**0.995146**
ROC-AUC	0.999991	0.999800	**0.999999**
PR-AUC	0.999752	0.993775	**0.999977**

B. Classification Robustness and Error Analysis

The confusion matrices in Figure 4 highlight the classification reliability of each model, especially for the rare islanding class. CNN misclassified two connected and one islanded window, while LSTM misclassified four connected and one islanded window. In contrast, CNN-LSTM misclassified only one connected and one islanded window, demonstrating superior fault discrimination. Class-wise metrics support this result, with CNN-LSTM achieving balanced precision and recall of 0.995 for both classes, whereas LSTM showed lower precision (0.981) for the islanded class, indicating a higher false-positive rate that may cause unnecessary distributed generation disconnections.

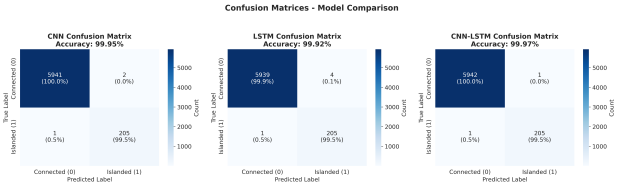

Fig. 4. Confusion Matrix of CNN

C. Training Dynamics and Convergence Behavior

The recorded training histories in Figure 6 reveal fundamentally different learning behaviors across the three architectures.

The CNN and hybrid CNN-LSTM models exhibited highly rapid and stable convergence. Both models achieved training and validation accuracies exceeding 99% within the first two epochs and stabilized shortly thereafter. Furthermore, their validation losses continued a steady decline without exhibiting signs of overfitting, validating the efficacy of the integrated dropout layers and L_2 regularization.

In contrast, the training trajectory of the standalone LSTM model was characterized by noticeable instability. Its validation accuracy fluctuated significantly throughout training and began to degrade after approximately 18 epochs. Consequently, the early stopping mechanism terminated its training process at epoch 22. This optimization instability, paired with its lower test-set precision, confirms that the LSTM architecture requires hierarchical convolutional preprocessing to extract clean, robust features from high-dimensional raw data.

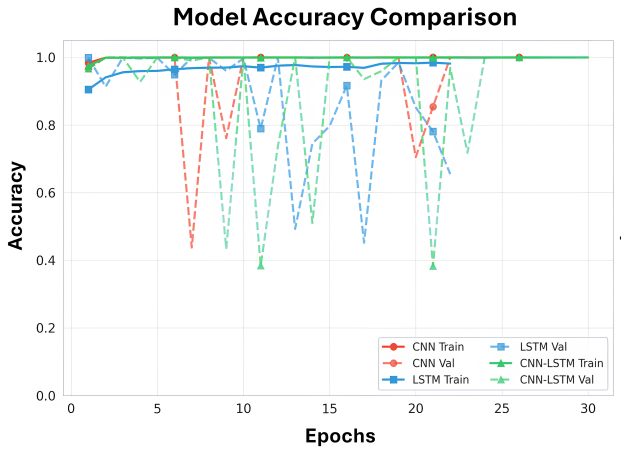

Fig. 5. Model Accuracy Comparison: comparisons for all models

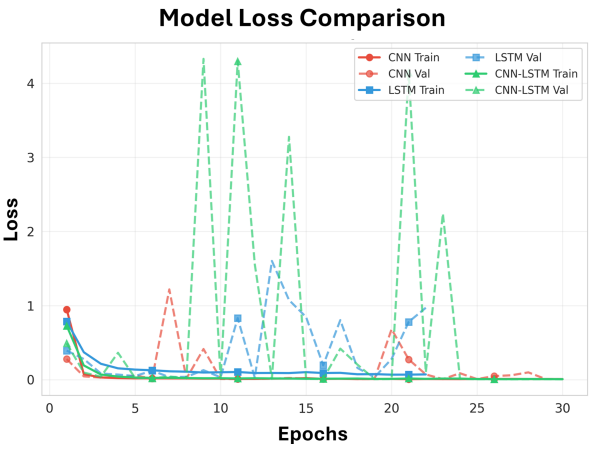

Fig. 6. Model Loss Comparisons: comparisons for all models

IV. Conclusion

This research proposed a data-driven islanding controller for renewable energy systems using a hybrid CNN-LSTM architecture. Three-phase voltage signals and LVRT thresholds were segmented into 100-sample windows and labeled using a threshold-based approach. On held-out test data, the proposed CNN-LSTM achieved an accuracy of 0.999675 and an F1-score of 0.995146, outperforming both CNN and LSTM models. The confusion matrix showed only two misclassifications across more than six thousand windows, demonstrating highly reliable islanding detection.

Although the CNN-LSTM models achieved strong test performance, their evaluation was limited to simulated data with fixed voltage dynamics, fixed LVRT thresholds, and class imbalance resulting from random sampling. The models, thus, were not exposed to any noise or variable LVRT values and had no exposure to other grid codes or unknown situations that could be encountered during deployment in the actual system. To improve the robustness of the classification process, the variation of both the threshold values and simulated measurements should be increased.

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