Deep Learning based Equivalent Electromagnetic Transient Model for Distribution Feeders with High Penetration of Distributed Energy Resources

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***Abstract*—The paper addresses the critical challenge of conducting slow and computationally intensive electromagnetic transient (EMT) simulations in distribution feeders with high penetration of distributed energy resources (DER). Traditional EMT studies are hampered by the complexity of modeling diverse inverter-based DER types and their collective behaviors. To overcome this, authors developed a two-stage deep neural network (DNN) model—first using a gated recurrent unit (GRU) network to predict DER tripping and then a long short-term memory (LSTM) network to estimate three-phase current responses. The model was successfully integrated into PSCAD through a co-simulation framework with negligible communication overhead, delivering near real-time simulation speeds approximately 30 times faster than conventional methods. This innovative approach not only maintained strong accuracy (with prediction errors typically below 4%) but also enabled practical, scalable EMT analyses for DER-affected system operator studies.**

***Index Terms*—Deep Neural Network, Distributed Energy Resources, Electromagnetic Transient Simulation, Inverter-Based Resources, Model Aggregation.**

I. Introduction

Driven by evolving policy mandates and the increasing impacts of climate change, renewable energy resources are being rapidly integrated into modern transmission and distribution (T&D) systems. A significant portion of these resources are inverter-based distributed energy resources (DERs), which include behind-the-meter single-phase solar photovoltaic systems and battery storage, as well as larger three-phase DERs installed at commercial and industrial facilities. These inverter-based resources are geographically dispersed and interconnected at various points along the distribution network, causing them to experience different voltage conditions during a fault event on the transmission grid. Because they are manufactured with proprietary control algorithms and they adhere to different interconnection standards — such as IEEE 1547-2003 and IEEE 1547-2018 — they exhibit varying ride-through capabilities during system disturbances, with some units maintaining grid connection longer than others. Z. Cheng et al. performed a comparison between the inverter responses from various inverter manufacturers in [1], which reveals inconsistent inverter ride-through responses and challenges in dealing with black-box proprietary inverter models.

As DER penetration levels increase, many distribution feeders are approaching or even exceeding 100% DER penetration. Under such high-penetration conditions, the feeders can collectively influence transmission-level dynamics by exporting reactive power through the T&D interface. Consequently, it is becoming essential for system operators to explicitly include distribution feeders in transmission-level planning studies to accurately capture their aggregate effects. The growing complexity of inverter-based resources (IBRs) and their widespread deployment have led operators to rely increasingly on electromagnetic transient (EMT) simulation tools, utilizing manufacturer-provided black-box inverter models to assess system behavior. However, performing detailed EMT studies that include the full transmission network, all black-box IBR models, and detailed distribution systems down to the residential level is computationally prohibitive for commercially available simulation software. Therefore, developing accurate equivalent models at the T&D interface is crucial. Such models must represent the collective response of distribution feeders and downstream DERs, capturing key dynamics such as partial DER tripping during disturbances, the aggregate contributions from diverse interconnection locations, and the varied inverter control characteristics across different manufacturers and standard compliances.

This paper addresses the aforementioned challenge by developing a deep learning–based, data-driven equivalent model capable of representing the collective response of a distribution feeder under transmission-level disturbances. The proposed model operates in the time domain and is implemented as an EMT model that can be directly integrated into commercial EMT simulation tools such as PSCAD. Previous studies have demonstrated the potential of deep learning techniques for modeling IBRs and distribution systems. For example, F. Calero et al. developed an aggregated battery energy storage system black-box model using two neural networks (NNs)—one for active power and another for reactive power [2]. C. Cai et al. proposed a Long Short-Term Memory (LSTM) recurrent neural network to create an equivalent model for a microgrid [3]. Other researchers have applied deep learning approaches to model distribution systems with DERs [4]–[6].

However, the common limitation of these prior works is that

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their data-driven models operate only in the phasor domain, restricting their use to quasi-steady-state studies such as power flow analysis, DER hosting capacity evaluation, and volt–VAR optimization. Only a few studies have attempted to develop deep learning–based models for time-domain EMT simulation. For instance, Kaufhold et al. [7] proposed an equivalent deep learning model for a single PV facility, but the model was trained and validated solely under steady-state operating conditions, excluding short-circuit and transient responses from its modeling scope.

The authors of this paper have previously pioneered the concept of deep learning–based EMT modeling for fault and transient studies, as described in a recent U.S. patent application [8]. That earlier work presented an LSTM-based model representing a single IBR facility. Building upon that foundation, the present paper extends the methodology to develop a physics-informed deep neural network (DNN) architecture capable of representing an entire distribution feeder with 100% DER penetration. Compared with existing literature, this study makes the following key contributions:

- Development of a time-domain EMT equivalent model that accurately captures steady-state, transient, and fault dynamics of a feeder with high DER penetration.
- Introduction of a physics-informed, two-stage DNN architecture, where a gated recurrent unit (GRU) network predicts DER tripping behavior, followed by an LSTM network that estimates three-phase current responses.
- Validation of the proposed two-stage DNN time-domain EMT model against detailed EMT simulations incorporating realistic, manufacturer-provided black-box inverter models, demonstrating its effectiveness and generalization capability.
- Demonstration that the proposed two-stage DNN model can be seamlessly integrated with commercially available EMT simulation platforms and achieve near real-time simulation performance, enabling its practical application in large-scale system studies.

II. Benchmark Systems

To prototype the DNN modeling approach, authors has created an elaborate T&D system in PSCAD with high penetration of DER. As shown in Fig. 1, the transmission system is modeled as the standard IEEE 14-bus system, whereas the distribution system is modeled as the IEEE 34-bus system. The feeder head (BUS-1 in the IEEE 34-bus model) is connected to BUS-13 in the IEEE 14-bus transmission system as an additional load.

To create high DER penetration scenarios, the team added three-phase and single-phase inverter-based DER at locations shown in Fig. 1. Inverter manufacturers provide black-box models to model all three-phase and single-phase DERs. Our system includes 10 single-phase DER locations. Each site features three independently controlled single-phase inverters, contributing to a 50 kVA installation capacity per location, for a total single-phase DER capacity of 500 kVA. The low-voltage ride-through (LVRT) characteristics of all single-phase inverters

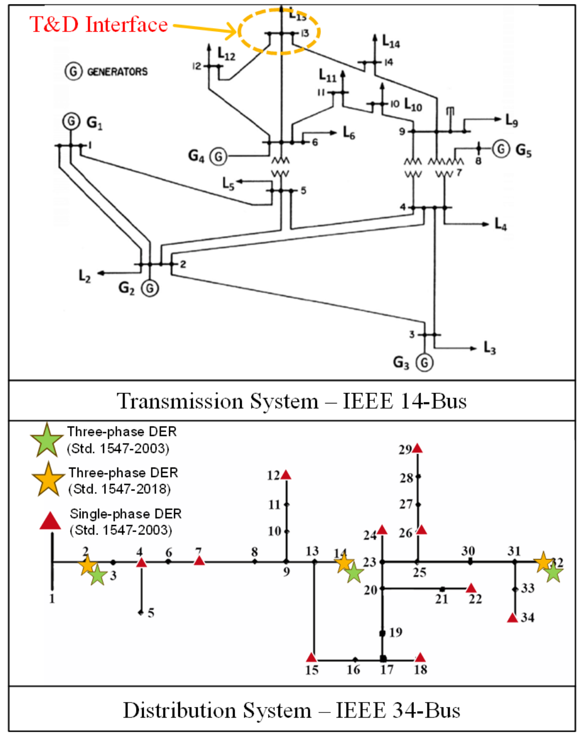

Fig. 1. T&D Benchmark System.

are configured to the IEEE 1547-2003 standard. For three-phase DERs, we have three locations. Each of these locations is equipped with two independently controlled three-phase inverters, with a combined capacity of 1 MVA per location. At each of these three-phase sites, one inverter (representing 30% of the local capacity) is configured to the IEEE 1547-2003 standard, while the other inverter (accounting for 70% of the capacity) adheres to the IEEE 1547-2018 standard.

III. Test Scenarios and Training/Testing Data Generation

A. Test Scenarios

System operator planning studies typically include N-1 scenarios in addition to normal system conditions. Therefore, the developed DNN model should remain accurate under both normal and N-1 scenarios. In this paper, we have created three N-1 conditions (line outage) near the T&D interface (BUS-13) in the transmission system, i.e., Bus 12–Bus 13, Bus 6–Bus 13, and Bus 13–Bus 14 line outages. In this paper, we developed a total of 1,200 test scenarios (13 GB in size), comprising 300 scenarios for each system condition, i.e., normal and three N-1 conditions as mentioned previously. For each scenario, we developed an automation test script to simulate fault events across all 14 buses in the transmission system. We simulated four fault types at each bus: AG, BC, ABC, and CAG. For every fault event, the fault inception angle was randomly generated between 0 and 90 degrees, and the fault duration was varied across 10 specific values: 5 cycles, 0.25s, 0.5s, 0.75s, 1.1s, 1.5s, 1.6s, 1.75s, 2.1s, and 2.5s.

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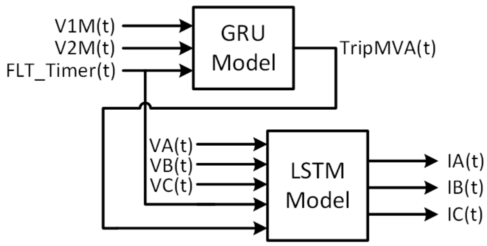

Fig. 2. 2-Stage DNN Model Structure for Aggregated DER Modeling.

These diverse fault configurations and durations were carefully selected to comprehensively evaluate DER LVRT responses.

B. Training and Testing Data Generation

The benchmark system created in this paper is highly computationally intensive. To efficiently study the test scenarios and generate training data, the team has decoupled the benchmark system and applied parallel processing techniques to speed up the simulation. The core electrical network (14-bus and 34-bus) is isolated and simulated on a single CPU core. In contrast, individual inverter-based DERs are simulated on separate CPU cores. This architecture also enables the inverter-based DERs to be simulated at different time steps, if necessary. In our simulation, the main electrical system is simulated at a 50 μS time step, while the DERs are simulated at 16.67 μS and 20 μS per the manufacturer's black-box model requirements. The simulation speed is approximately 29 seconds per simulated second in PSCAD using a 96-core high-performance computer.

IV. Data-Driven Modeling Approach

A. Premise

The data-driven modeling approach developed in this project applies to grid-following inverter-based DER. A typical grid-following inverter is commonly characterized as a voltage-controlled current source device. Therefore, the basic concept of the data-driven inverter model is to predict three-phase current using three-phase voltage from the previous time step.

B. Physics-Informed DNN Model Structure

For this paper, the DNN model must capture not only the initial LVRT transient responses but also the partial DER tripping behaviors during sustained low-voltage disturbances. Therefore, the team enhanced the basic voltage-controlled current source DNN modeling concept in [8] to specifically incorporate information relevant to capturing these partial DER tripping behaviors.

Fig. 2 depicts the enhanced 2-stage DNN model structure: The Stage-1 DNN is using voltage magnitude and fault duration information to predict the tripped DER amount in terms of MVA. There are three inputs: $V1M(t)$ — a time series of positive sequence voltage at the feeder head in per unit. $V2M(t)$ — time series of negative sequence voltage at the feeder head in per unit. $FLT_{Timer}(t)$ — elapsed time since fault inception in seconds. The DNN output is $TIRP_{MVA}(t)$ — time series of tripped DER amount in MVA.

The intuition behind the stage-1 DNN is that the DER under-voltage or over-voltage tripping behaviors depend solely on the integral of voltage magnitude over time. The positive sequence voltage is crucial for predicting the tripping of all DERs, while the negative sequence voltage helps predict the tripping of single-phase DERs specifically.

GRU is a type of recurrent neural network (RNN) architecture, known for its ability to handle sequential data and mitigate the vanishing gradient problem, which can hinder the training of standard RNNs on long sequences. Introduced as a simpler alternative to LSTM models. It is proven to be an efficient DNN model for tripped DER prediction.

The Stage-2 DNN is using three-phase voltage, fault duration, and tripped DER amount to predict three-phase current. There are five inputs: $VA(t)$, $VB(t)$, and $VC(t)$ — three-phase voltages at the feeder head in per unit. $FLT_{Timer}(t)$ — elapsed time since fault inception in seconds. $TIRP_{MVA}(t)$ — time series of tripped DER amount in MVA. There are three outputs: $IA(t)$, $IB(t)$, and $IC(t)$ — three-phase current at the feeder head in per unit.

The intuition behind the stage-2 DNN model is that the grid-following inverters function as voltage-controlled current source devices, using measured voltage to predict current output. To accurately capture DER partial or full tripping behaviors, information regarding fault duration and the amount of tripped DERs is crucial.

An LSTM model is a type of recurrent neural network (RNN) particularly well-suited for processing and predicting sequences of data. It excels at capturing long-term dependencies in sequential data. It is proven to be a very good model for instantaneous current prediction.

As illustrated above, the intuitions behind the DNN model are driven by the physics of the power system and the inverter. The model structure design can be explained, and the intermediate prediction variable, i.e., tripped DER MVA, has physical meaning.

C. DNN Model Training and Testing

The training and testing of the DNN models in this project are performed using MATLAB 2024a and an NVIDIA RTX A5000 GPU with 24 GB of RAM. The simulated data described in Section III is divided into 800 training (66.67%) and 400 testing (33.33%) datasets.

1) Stage-1 GRU Model Training and Testing: The training process took 1 hour and 22 minutes. Fig. 3 depicts the overall accuracy of the stage-1 GRU model. The prediction accuracy is evaluated by calculating the Mean Absolute Percentage Error (MAPE). The absolute error between reference and prediction is calculated on a point-by-point basis in the time domain and divided by the total DER MVA. Eventually, the absolute percentage errors are averaged, producing a single scalar value for each test scenario. According to the histogram in Fig. 3, most of the test scenarios have MAPE smaller than 3% - 360 cases out of 400. The worst MAPE for this model is around 7%. The average MAPE for all 400 cases is 0.81%. Example predictions are given in Fig. 3, the blue signal traces

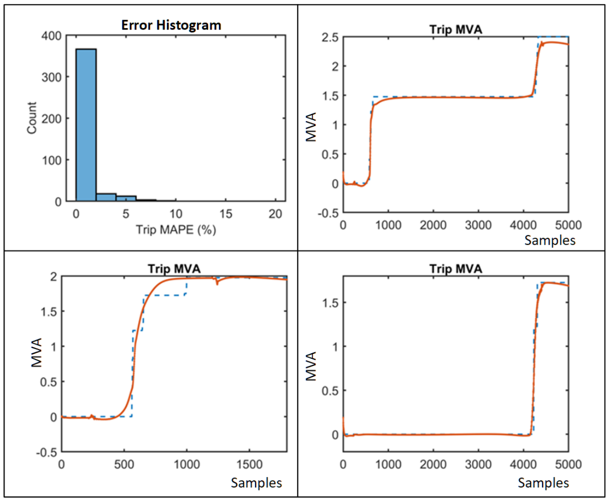

Fig. 3. Overall Accuracy of the Stage-1 GRU Model and Sample Tripped DER Predictions.

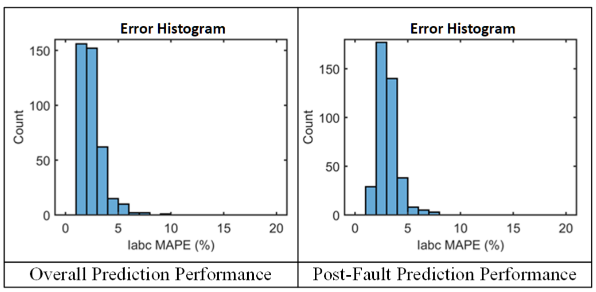

Fig. 4. Accuracy of the Stage-2 LSTM Model.

are tripped DER MVA recorded from the detailed PSCAD simulation, whereas the red signal traces are predictions from the DNN model. It is apparent that the prediction can closely track the detailed PSCAD simulation. Notably, the DNN model generates tripped DER MVA levels with smooth transitions, whereas the detailed PSCAD simulation generates step changes. This difference will not produce a notable error in the final predictions.

2) Stage-2 LSTM Model Training and Testing: The Stage-2 DNN model is engineered to predict three-phase instantaneous current, leveraging inputs such as the three-phase feeder head voltage, estimated DER tripping events, and fault duration.The model's predictive accuracy is thoroughly evaluated in Fig. 4 using the MAPE. Performance is categorized into two aspects:

- Overall prediction accuracy: A vast majority of cases, specifically 360 out of 400, exhibit an overall MAPE below 4%. Only a small number of edge cases fall within the 5% to 10% MAPE range.
- Post-fault prediction accuracy: The model maintains comparable accuracy levels for post-fault predictions, with the median MAPE increasing by a slight 1%, compared with the overall accuracy.

An illustrative example of the DNN model's capabilities is presented in Fig. 5, showcasing its predictions during an unbalanced LVRT event where the feeder experienced partial tripping. This example highlights the DNN model's proficiency in accurately capturing all LVRT transients and the specific partial tripping behavior observed in the B phase.

3) Optimizing DNN Model Performance: To achieve the accuracy in Fig. 4, the authors have been continuously refining the training process and resolving edge cases. Notably, the following troubleshooting and model optimization steps were undertaken.

Problem 1: DNN model trained with normal condition data showed subpar accuracy performance for N-1 conditions.

Troubleshooting steps and lessons learned 1:

- Include N-1 cases in the training data. However, the training dataset becomes too large.
- Reduce the training dataset by selecting representative fault locations, e.g., bus 1, 5, 6, 9, 13. The goal is to ensure that the training data encompasses the parameter space as thoroughly as possible. For example, based on our observation, the edge cases ($\geq$20% MAPE) are isolated interior points in the parameter space, as shown in Fig. 6. No training data samples are shadowing them.
- Intelligently tweaking the training data mix to cover the parameter space and re-training the model solved this issue.

Problem 2: Initial version of the DNN model (single-stage LSTM model used in [8]) struggles to predict partial tripping behavior and post-fault load current.

Troubleshooting steps and lessons learned 2:

- Added the fault duration input to the LSTM model. This significantly improved the model's ability to predict partial tripping behaviors. However, the post-fault current prediction is still not ideal ($\geq$10% MAPE).
- Use tripped DER MVA as input significantly improved the post-fault prediction accuracy. The team developed a two-stage model.
- The prediction of tripped DER was initially made with three-phase instantaneous voltage signals and fault duration. However, the prediction was not ideal. This is due to the input voltage signals being periodic cosine waves. The DNN model struggles to transform the input signals to DC signals.
- The team redesigned the stage-1 DNN model to use magnitudes of positive sequence and negative sequence voltage. This resolved the issue with the tripped DER prediction.

V. Integration of DNN Model in EMT Simulation

The team has developed a robust integration workflow to seamlessly incorporate the DNN model into PSCAD, utilizing PSCAD's native co-simulation interface. This process involves several key steps: (1) DNN Model Development and Configuration (MATLAB Simulink): The DNN model is initially developed, trained, and configured within the MATLAB Simulink environment. (2) C/C++ Code Generation (Embedded Coder): Leveraging the Embedded Coder toolbox in MATLAB, the

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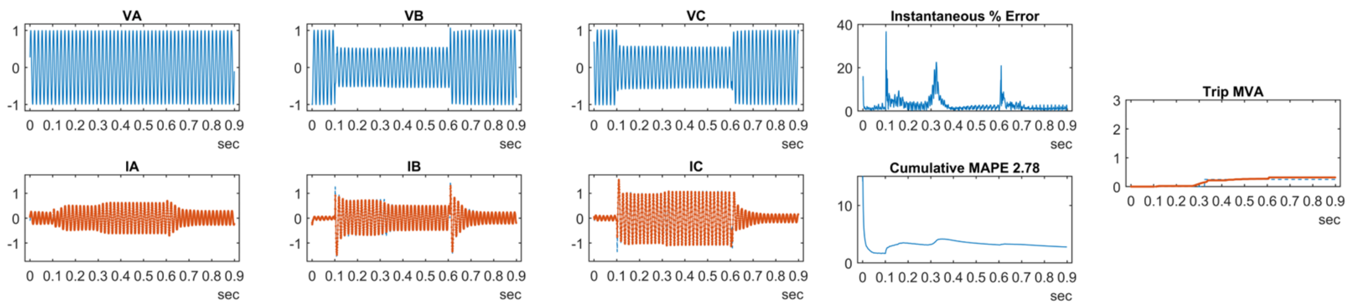

Fig. 5. Example Prediction of the Stage-2 LSTM Model: Voltages and currents, MAPE, and Tripped DER. Blue Signals - PSCAD; Red signals - DNN.

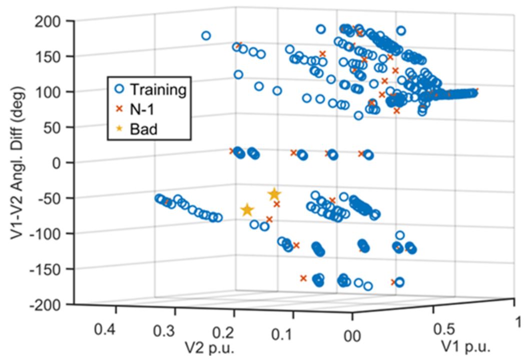

Fig. 6. 3-D Parameter Space and Training Data Coverage.

trained DNN model is then converted into highly optimized C/C++ code. (3) External Application Packaging and Interface: The generated C/C++ code is subsequently packaged as an external application. This application is specifically designed to interface with PSCAD through its co-simulation capabilities. (4) PSCAD Simulation Setup: Finally, the co-simulation environment and electrical interface (voltage-controlled current source) are configured within PSCAD to enable integrated operation with the external DNN model application.

The native PSCAD co-simulation significantly optimizes communication efficiency by supporting a shared memory mode. In this mode, the main PSCAD simulation communicates with an external application, such as our DNN model, directly through shared memory in RAM. This approach introduces only negligible communication overhead, typically 1-2 μS. In this paper, the feeder is modeled as a voltage-controlled current source. Voltage measurements and fault duration data are transmitted to a co-simulation interface, which then relays this information to the DNN model. The DNN model subsequently returns predictions for tripped DER and three-phase current to the PSCAD simulation. A key advantage of this setup is the ability to increase the PSCAD simulation time step up to 500 μS, aligning with the 500 μS resolution of the DNN model's training data. This significantly accelerates simulation speed, achieving near real-time performance where approximately one second of simulation time corresponds to one second of real time. This is thirty times faster than the detailed PSCAD simulation speed discussed in Section III.

VI. Conclusion

This paper developed a deep learning–based equivalent EMT model for distribution feeders with high DER penetration. A two-stage DNN architecture—combining a GRU network for DER tripping prediction and an LSTM network for three-phase current prediction—accurately captured both transient and steady-state dynamics at the feeder head. Validation against detailed PSCAD simulations showed high accuracy, with an average MAPE of 4%. The model's seamless co-simulation integration enabled near real-time performance, approximately thirty times faster than traditional EMT studies with detailed feeder model using parallel processing. The proposed framework provides a scalable and efficient approach for system-level EMT analyses, facilitating practical large-scale studies of DER-integrated power systems.

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