Novel Approach to PV Inverter Modeling and Simulation Leveraging Experiments, Learning Based Modeling and Co-Simulation

Preprint

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***Abstract*— Photovoltaic (PV) inverter manufacturers use custom, proprietary control approaches and topologies in their inverter design. The proprietary nature of these approaches makes it challenging to share electromagnetic transients (EMT) domain models for system studies. This research work presents an approach to develop EMT models from experimental data. We use novel approach in experimental design, high fidelity data collection, use of learning-based modeling, and co-simulation to reduce the time taken to develop an EMT model for an inverter under test (IUT). We used a 20 kW off-the-shelf grid following PV inverter and subjected the inverter to controlled tests. The tests include voltage and frequency step changes, as well as solar irradiance variations. The recorded high frequency data were used to train a neural network model representing the dynamic behavior of the IUT. The model was subsequently imported into an EMT tool using co-simulation techniques, and thus completing the modeling effort.**

Keywords*— *Black box inverter modeling, Co-simulation, Electromagnetic transients simulation, Inverter, Inverter under test, Machine learning-based modelling, Photovoltaic

I. INTRODUCTION

Solar photovoltaic (PV) inverters are becoming a key distributed energy resource (DER) and a key power system component both in distribution and sub-transmission voltage levels [1]. Multiple standards across the globe have aimed to standardize the inverter controls and thus its dynamic behavior to system changes [2]–[4]. Accurately modeling these PV inverters in electromagnetic transients (EMT) domain is critical for system studies performed by utilities. Accurate representation of inverters in system studies can be particularly challenging if the inverter manufacturers do not intend to share their proprietary power electronics models and the proprietary inverter controls. Yet, developing an accurate inverter model is time-intensive and error-prone, due to the combination of both discrete and continuous components inherent in inverters [5],[6]. In addition, PV inverter manufacturers employ custom, proprietary control approaches and topologies in their designs, preventing the sharing accurate models for comprehensive system studies [5].

One approach to DER integration analysis and design in complex power system is the EMT simulation. These simulations are crucial for assessing the dynamic behavior of power systems, particularly focusing on electromagnetic phenomena. However, accurate EMT simulations pose challenges, including longer computation times due to numerical integration time-steps and high-precision models. These challenges arise from solving complex systems of differential and algebraic equations for nonlinear functions, as well as updating matrices because of switching events [6]–[8].

This work aims to leverage the developments in PV inverter experimental science to run exhaustive experiments on the inverters. The aim is to ensure that the experiments can emulate the power system dynamics of interest dictated by a user. High fidelity data will be collected from the experiments on both AC side and DC side of the experiments. This work has created a list of experiments suitable for modeling goals but the experiments need not be limited to the ones provided in this work. More experiments can be performed, and the data can be used to enhance the learning-based models.

The use of machine learning (ML) to develop models is considered as a promising solution for addressing power system component modeling when high fidelity data sets are available [9]. In this study, ML technique is used to develop an inverter model using the high fidelity model collected in the lab experiments.

The motivation behind this initiative is fueled by several key factors. Firstly, ML processes represent promising solutions to tackle challenges in power system modeling and analysis since they offer an alternative to traditional physics-based modeling methods, which often rely on simplifications and linearization [10]. This approach combines data-driven models with ML and physical/mathematical principles, forming an advanced hybrid modeling and analysis method [10]. Leveraging ML's ability to learn from data-rich environments with minimal dependence on mathematical models provides an effective solution to modern power system challenges [11]. Thus, improving the accuracy, reliability, and dynamic response [12] of the inverter.

Despite the growing interest in integrating ML with power systems, the limited number of real-world applications suggests that a gap still exists between research and practical implementation [10].

The limited practical implementation of ML underscores the significance of our study introducing a practical approach that combines leaning-based modeling of inverters and the use of these models in EMT simulation for accurate power system modeling and analysis. This approach is commonly known as collaborative simulation, or alternatively, co-simulation that address the challenges stemming from the extensive heterogeneity of EMT models [13], [14] allowing an accurate modeling of the dynamic behavior of smart grids with their diverse components [14] and addressing each specific component via its own specialized simulation tool [6].

The primary objective of this study is to develop an accurate inverter model through the use of exhaustive experiments, high frequency data collection and the use of ML to develop an EMT domain model and leverage co-simulation to integrate the ML-based model into an EMT tool. The ML based model can recreate current references based on the AC voltage, DC voltage and DC current. Since, EMT tools cannot inherently take ML-based models, we use novel co-simulation of the developed ML-based model with a commercial off-the-shelf EMT tool.

The proposed approach is depicted by figure 1.

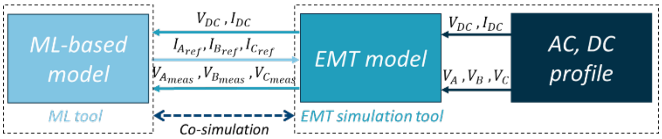

Fig. 1. Co-simulation of ML-based PV inverter model and EMT tool to accurately represent the inverter under test

II. Setup to Run Experiments on PV Inverter Under Study

The inverter under test for this work is a 20 kW off-the-shelf grid-following PV inverter. The experimental setup used a controllable AC supply and a controllable DC supply at NREL's Energy Systems Integration Facility [15]. The experimental setup for these tests is show in figure 2. Two sets of tests were performed on the inverter. In Test 1, voltage step changes were introduced on the AC voltage within the range of 0.88 pu to 1.09 pu, with a step size of 0.025 pu, while the AC frequency was maintained at 60 Hz. In Test 2, frequency changes were made on the AC voltage while keeping the magnitude unchanged. The frequency changes were within the range of 59.4 Hz and 60.45 Hz, with a step size of 0.2 Hz. Both tests were conducted under varying the PV insolation on the DC side. The PV insolation was kept at 25%, 50%, and 75% with the 100% load condition excluded due to limitations in the DC supply. More details on the experiment can be found in [16] and the data set can also be found in [15]. More changes can be made on the AC and DC side depending on the modeling requirements from the user.

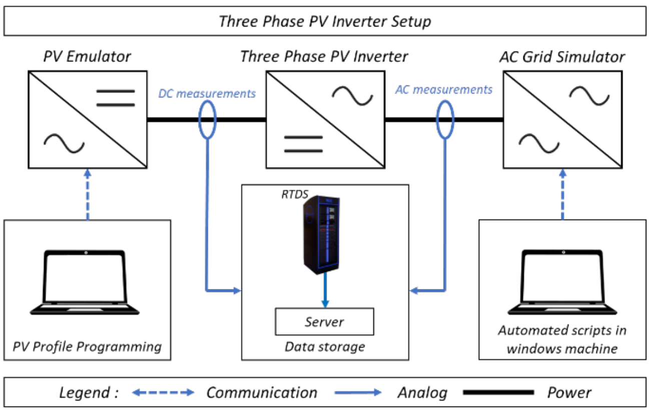

Fig. 2. Setup to run exhaustive experiments and collect high frequency data for the three phase PV inverter under test

The recorded data encompasses a series of parameters, including the time stamp, the three phase voltages V_A, V_B, V_C, the three phase currents I_A, I_B, I_C and the DC signals V_{DC}, I_{DC}.

More details giving a comprehensive understanding of the experimental setup, data gathering process, and analysis is provided in reference [16].

This study mainly focuses on the voltage step change dataset from Test 1. This data, totaling 1.85 GB, required extensive computational time. Consequently, it was partitioned into 10 cycles, each measuring 1.05 MB. As a result, a single cycle corresponds to 49.95 ms, and 10 cycles span 499.95 ms. This dataset is stored in a CSV file.

III. Machine Learning-Based Model

To achieve the main goal of accurately representing the inverter behavior ML tool was used to derive a model from the data collected during the experiments.

The inverter model is generated using TensorFlow™, via the Keras™ interface. The resulting model is integrated at the calculation step for generating the three phase reference currents from Python™ through a neural network application programming interface (API). This model takes the measured three-phase voltages $V_{A_{meas}}$, $V_{B_{meas}}$, $V_{C_{meas}}$, and the DC voltage and current V_{DC}, I_{DC} as inputs, and predict the three-phase current references $I_{A_{ref}}$, $I_{B_{ref}}$, $I_{C_{ref}}$ accordingly as shown in the figure 3.

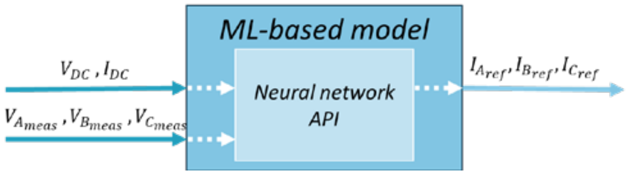

Fig. 3. ML-based model synopsis

In this study, the neural network API is treated as a black box. However, more details giving a comprehensive understanding of ML-based model is provided in reference [16], [17]. Upon integrating the ML-based model in the Python™ script, the resulting current references output from the Python™ script are depicted in figure 4. It is observed in this figure that the AC reference currents constitute approximately 63.5% of the DC current.

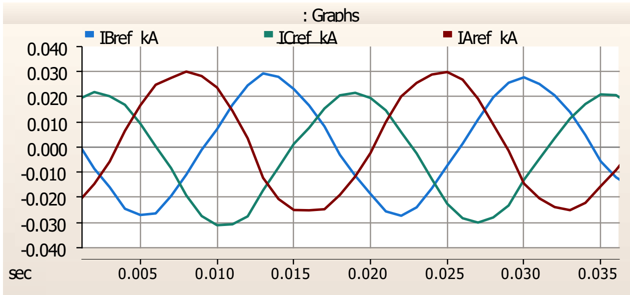

Fig. 4. Learning based Python™ script outputs

IV. Co-Simulation Approach to Integrate ML-Based Model in EMT Simulator

A. EMT Model

The EMT model is implemented on PSCAD™ software and consists of two main parts. The first part represents the EMT model itself, targeting a grid-connected three-phase grid-following inverter. The inverter is modeled in Python™ and the current references from the model are injected using a controlled current source in the EMT model as shown in figure

5. In this model, the three-phase currents in the circuit, along with the three-phase voltages on the grid side are measured. In addition, the RMS values are also calculated. The grid is represented by an external input-based voltage source. The input signal to this voltage source is imported from a dataset. This allows the user to play AC voltages stored in the experiments. The control signal for the current source is external and comes from the ML-based model.

The implemented EMT model is depicted by figure 5.

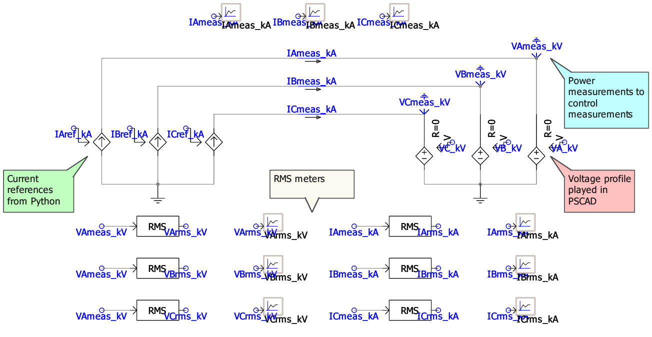

Fig. 5. EMT circuit used in co-simulation

The data importing is achieved using a file read element to read the formatted CSV file. The data read from the CSV file is then converted within PSCAD™ to kV and kA to maintain consistency. The simulation results related to 1 cycle data importing are presented in figure 6.

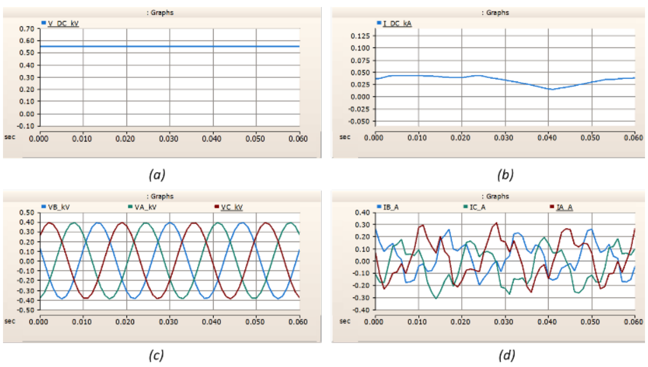

Fig. 6. Data importing simulation results (a) DC voltage, (b) DC current, (c) three phase AC voltages and (d) three phase currents (showing startup)

The second part of the EMT model showcases the co-simulation interface between the EMT tool and the ML-based model based on the co-simulation component in PSCAD™.

The co-simulation component enables the exchange of data between the EMT model and an external application, using the PSCAD™ inter-application communications control architecture known as Communication Fabric (ComFab). A client ID is assigned to the co-simulation component, serving to identify the client application—in this case, the Python™ application. The client ID also plays a role in generating and identifying the configuration file to establish the connection with the external application. The co-simulation component is configured with an array of dimension 5 for sending data from PSCAD™ to Python™ and an array of dimension 4 for receiving data from Python™ to PSCAD™. The data sent includes 3 AC voltages, one DC voltage and one DC current. All these five values are from experiment. This can also be easily replaced with controlled voltage sources for additional experiments. The received data encompasses the three-phase currents, which will serve as control signals for the controlled current sources, as well as a test variable for confirming the accurate data transfer from Python™ to PSCAD™.

The implemented ML/EMT models co-simulation interface is depicted in figure 7.

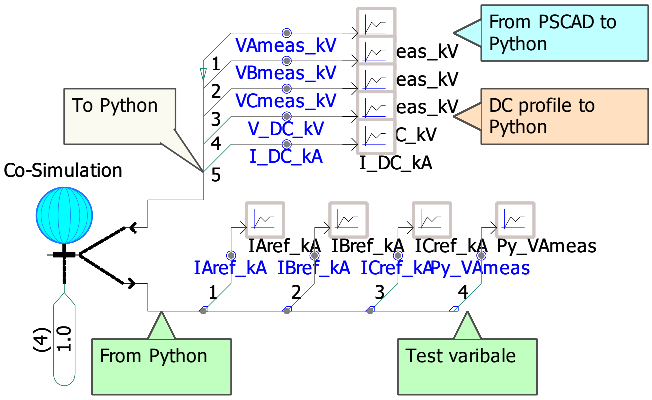

Fig. 7. Python™/PSCAD™ co-simulation interface

The ML-based model outputs for the co-simulation illustrated in figure 8, show the three-phase current references characterizing the inverter's behavior and a test variable, showcasing one of the voltages transmitted from PSCAD™ to Python™ and relayed from Python™ to PSCAD™. This serves as confirmation that the transmitted variables are accurately read within the Python™ environment.

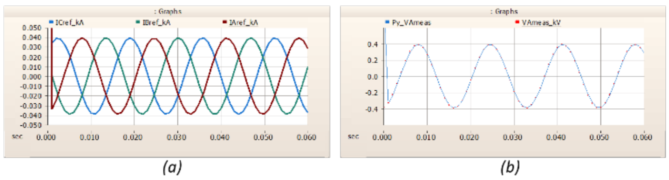

Fig. 8. Python™ outputs for the co-simulation (a) test variable and (b) three phase current references

B. *Cosimulation with ML-based model*

The external application co-simulated along with the EMT model is implemented in Python™. Within the Python™ script, the ML-based model is integrated into the co-simulation framework, becoming an integral part of the computation process. This integration takes place within the main co-simulation function of the program.

The co-simulation function uses two arguments: the path to the configuration file and the total runtime for the EMT model simulation. To ensure the validity of these arguments, subprocesses perform checks to verify the existence of the configuration file specified by the user and to confirm that it is associated with a valid client ID. Additionally, the subprocesses ascertain that the user-provided runtime value is positive.

Once the arguments are validated, a co-simulation context is set up using the configuration file and the communication channel is identified. Initialization of all time-related variables is then performed. Subsequently, the main program loop is initiated, and keeps running until the time variable reaches the specified run time.

Within this loop, data from the EMT model is read at designated time intervals and from specified channel indexes. This data are then used for the calculations to generate the ML-based model outputs that represent the control signals for the controlled current source in PSCAD™. The time variable is iteratively incremented to advance the simulation time. The values of the output channels are updated and sent to EMT model at the specified time points. The co-simulation process flow is shown in figure 9.

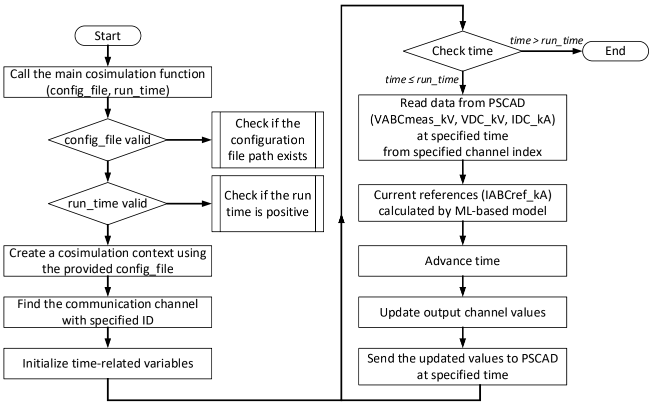

Fig. 9. Co-simulation framework flowchart

This co-simulation framework provides the flexibility to incorporate any ML application at the calculation step for generating Python™ outputs. For co-simulation purposes, the Python™ application must be included as an external process within the simulation sets in PSCAD™. This involves naming the application in accordance with the assigned client ID as well as indicating the Python™ executable file as the process to be launched. Two arguments are also to be set when including the external process: the Python™ script associated with the application and the configuration file linked to the client ID.

C. Co-simulation results

In this section, the key components that construct the co-simulation framework are outlined, emphasizing the integration of a ML-based model, using neural network API for a prediction purpose, with an EMT domain model based on imported experimental data. Figure 10 illustrates the data exchange between the different environments.

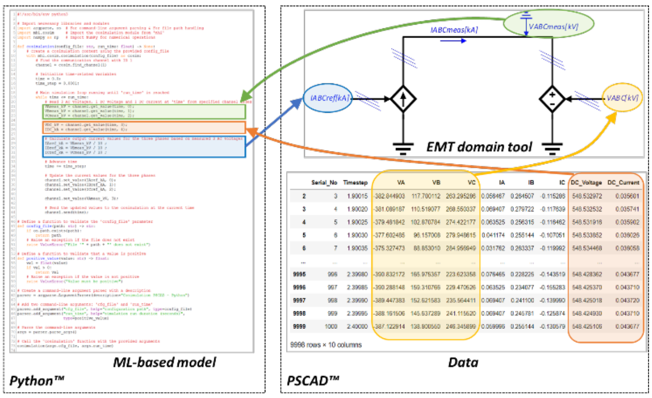

Fig. 10. Exchanged data in the context of the co-simulation project

The simulation results of this project are depicted in figure 11 and show the plotted outcomes of the EMT model, mainly the three phase voltages and current measured within the circuit, as well as their RMS calculations.

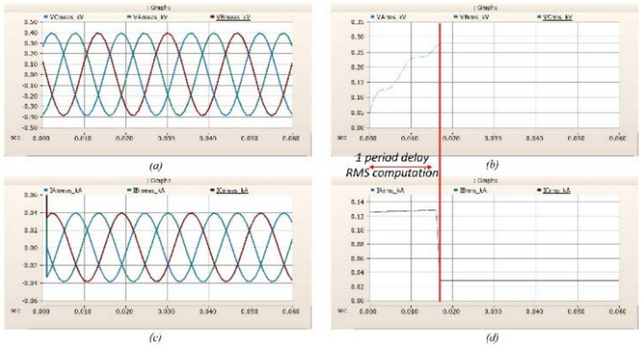

Fig. 11. Simulation results of the EMT model (a) Three phase measured voltages (b) and their RMS calculation - (c) three phase measured currents (d) and their RMS calculation

V. Conclusion

The significance of this research lies in addressing the critical need for accurate inverter modeling in EMT domain. The current lack of accurate and comprehensive inverter models from manufacturers poses a considerable challenge for a comprehensive analysis of power systems. While classical approaches offer the possibility of obtaining accurate models, their inherent time-consuming nature highlights the need for more efficient methodologies.

This research work introduces a rapid and innovative method to obtain inverter model within a week, from hardware reception to modeling in an EMT domain tool. The proposed approach employs an ML-based model, derived using inverter experiments taking a maximum of 1 hour to collect sufficient data. Since the ML-based models might lack mathematical structure that are sufficient to be integrated into commercial off-the-shelf EMT tools, a co-simulation between the EMT model and a ML-based model was used. In essence, the paper offers a novel and rapid approach for achieving accurate inverter modeling using ML-based modeling to process experimental data and use the developed models through co-simulation between the ML-based model and an EMT domain tool.

Future perspectives include developing a more generic and exchangeable application that can be used on various EMT-type simulation tools, independent of the co-simulation interface. To achieve this, future work will be based on a well-defined open industry standard for coupling power system tools across different time domains and voltage levels with ML tools. Additionally, the digital real-time implementation of the standard-based co-simulation between the EMT model and ML-based model will provide a dynamic platform to emulate real-world conditions, testing and refining inverter models within scenarios that reproduce the complexities of actual grids.

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