A C-HIL based data-driven DC-DC power electronics converter model for system-level studies

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***Abstract*—We propose to exploit a Controller Hardware-In-the-Loop (C-HIL) digital twin of power electronics converters to acquire data for deriving a model that is usable in system-level studies. An enhanced neural network-based polytopic model (a black-box model) is used for this purpose. The choice of this model is motivated by its simplicity and the ability to conceal the converter's topology and control algorithm within its structure, thus ensuring the data privacy of power electronics converter manufacturers. The capability of the proposed approach to capture the primary dynamics of converters is demonstrated, and the approach is validated on an industrial DC-DC power electronics converter.**

***Index Terms*—power electronic converters, C-HIL, system identification, neural networks, polytopic models**

I. Introduction

Power electronics converter (PEC) manufacturers usually do not disclose detailed converter models for confidentiality reasons. This poses a challenge in deriving accurate and efficient models of PECs needed for their control design and system-level studies.

PECs model identification is challenging due to their non-linear and time-varying nature emerging from multiple switches configurations. Usually, a state-space averaging method is used to remove time-varying characteristics and describe converter dynamics through a non-linear mathematical model [1]. Non-linear system identification is a broad subject offering a number of approaches [2]. Some existing works focus on identifying PECs models for designing the best controller [3]. They are either using a linear model obtained by linearizing the state-space averaged model [4], or a non-linear model using specific approaches such as the Hammerstein models [1].

The scope of this paper is not to design a controller but rather to model the whole manufacturer device for use in system-level studies. Different techniques exist for this purpose. For instance, in [5], the authors developed a full neural network model of a buck converter. Although this technique yields good performance, the inherent dynamics are hidden within the neural network structure, which is not suitable for detecting causes of instabilities. In [6], authors proposed using polytopic models, a combination of linear models allowing to perform linear model analyses. However, the selection of linear models and how they are combined is often left as a user choice. In [7], an enhanced neural network-based polytopic model combines the universal approximator characteristic of neural networks with the linear models-based structure of polytopic models. The main drawback is the requirements of expensive measurement devices and measurement data that may not be easily available.

In this work, we consider the approach introduced in [7] and propose the use of the data acquisition on a C-HIL digital twin to eliminate the drawback of that approach. C-HIL connects a hardware control system, such as embedded microprocessors, to a digital device that performs simulation in real-time while exchanging signals with the hardware system. It allows for the system to be tested in a closed loop with an accuracy close to a complete hardware system experiment while conserving the flexibility of a simulation tool. C-HIL modeling is preferred to using the real power converter because it allows for fast and accurate testing of the system in a controlled environment without the need for costly and time-consuming physical tests.

While C-HIL models may not be appropriate for detailed system-level studies due to the need for significant computational resources, they allow for rapid and accurate data harvesting. We propose an approach where we extend the usage of C-HIL models for building black-box models that are suitable for system-level studies. We demonstrate the effectiveness of our approach by applying it to an industrial PEC and comparing the results with real measurements.

The paper is organized as follows. Section 2 provides an overview of the proposed procedure for the identification of the black-box model parameters. Section 3 describes the C-HIL model used for data acquisition. Section 4 presents the results of the experiments and compares the proposed model with real measurements. Finally, Section 5 concludes, summarizes the main findings, and discusses the potential applications.

II. Enhanced neural network-based polytopic model (*PMnet*)

To derive large signal black-box models of power electronics converters, we use a model architecture proposed recently in [7] and termed here as *PMnet*.

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A. The approach overview [7]

The approach is based on polytopic models, where multiple linear and time-invariant systems (LTI) responses are merged using a weighting function. A neural network-based weighting function is used for finding a better combination of LTI systems than conventional polytopic models using generic weighting functions [8]. The LTI systems considered are infinite impulse responses (IIR) for which the regression vector can be defined as

$$\begin{aligned}\boldsymbol{\varphi}[n] =& [-\hat{y}[n-1], ..., -\hat{y}[n-n_a], \\ & u[n], u[n-1], ..., u[n-n_b]]^T,\end{aligned} \tag{1}$$

where n is the time index.

The following tunable coefficients are considered:

$$\boldsymbol{\theta} = [a_1, ..., a_{n_a}, b_0, b_1, ..., b_{n_b}]^T, \tag{2}$$

such that the response of the LTI system at time n is:

$$\hat{y}[n] = \boldsymbol{\theta}^T \boldsymbol{\varphi}[n]. \tag{3}$$

For time-domain data, (3) can be solved using least squares methods to find the best coefficients $\boldsymbol{\theta}$ for minimizing discrepancies between the actual system output $y[n]$ and the predicted system output $\hat{y}[n]$ for every time index n. Introducing the time delay operator q^{-1}, the following notation is equivalent to (3):

$$\begin{aligned}\hat{y}[n] = & (b_0 + b_1 q^{-1} + \cdots + b_{n_b} q^{-n_b}) u[n] \\ & -(a_1 q^{-1} + \cdots + a_{n_a} q^{-n_a}) \hat{y}[n]\end{aligned} \tag{4}$$

and the input-output relation of a single-input single-output system (SISO) is defined as:

$$G(q) = \frac{b_0 + b_1 q^{-1} + \cdots + b_{n_b} q^{-n_b}}{1 + a_1 q^{-1} + \cdots + a_{n_a} q^{-n_a}}. \tag{5}$$

Black-box models of power converters can be seen as multi-ports systems, as shown in Fig. 1, which are described as multi-input multi-output systems (MIMO). Fig. 1 shows what is considered within the black-box model. It embeds the plant, with active and passive electrical components, and the controller driving active components. $\mathbf{y}(t)$ corresponds to measured signals used by the controller. α^{ref} are parameters based on which the controller gives commands. Inputs $\boldsymbol{u}[n]$ and outputs $\hat{\boldsymbol{y}}[n]$ can be reference values or electrical measurements. A general form of a MIMO system can be defined as:

$$\hat{\boldsymbol{y}}[n] = \mathcal{G}(q) \boldsymbol{u}[n], \tag{6}$$

where,

$$\begin{aligned}\hat{\boldsymbol{y}}[n] &= [\hat{y}_1[n], ..., \hat{y}_{n_y}[n]]^T \\ \boldsymbol{u}[n] &= [u_1[n], ..., u_{n_u}[n]]^T \\ \mathcal{G}(q) &= \begin{pmatrix} G_{11}(q) & \cdots & G_{1n_u}(q) \\ \vdots & \ddots & \vdots \\ G_{n_y 1}(q) & \cdots & G_{n_y n_u}(q) \end{pmatrix}\end{aligned} \tag{7}$$

The MIMO system $\mathcal{G}(q)$ is composed of a collection of linear SISO systems, meaning that it is incapable of representing nonlinear converter's behaviors. Using a single MIMO system to describe a converter's response across its entire operating range can thus result in suboptimal performance.

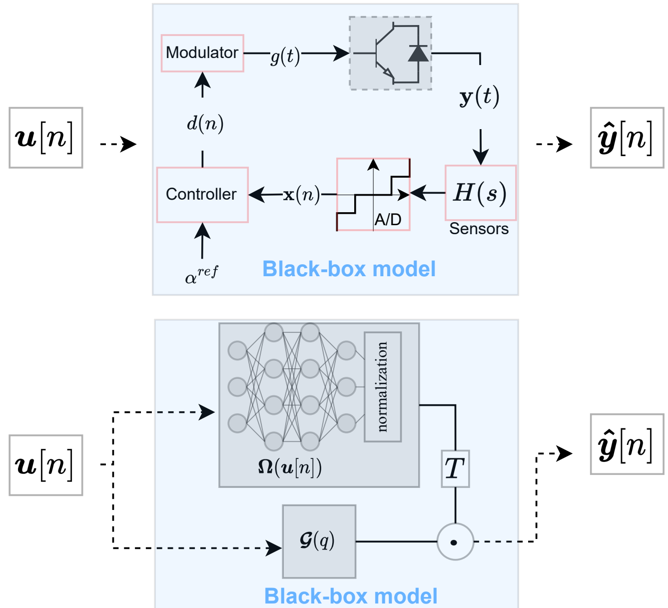

Fig. 1. An illustration of the considered black-box model.

The concept of the *PMnet* is to create multiple MIMO systems around different operating points, each with good performance in the vicinity of the point where it was identified. By wisely combining the responses of these MIMO systems, significantly better results can be achieved than with a single MIMO system alone. The various MIMO systems can be combined using a weighting function:

$$\boldsymbol{\omega} = \Omega(\boldsymbol{u}[n]) \in [0, 1]^N, \tag{8}$$

where $\boldsymbol{\omega} = [\omega_1, \cdots, \omega_N]^T$ with N the number of MIMO systems (named submodels hereafter). Every element of $\boldsymbol{\omega}$ takes a value between 0 and 1, and $||\boldsymbol{\omega}|| = 1$ to ensure one does not amplify nor attenuate the submodels responses. If $\boldsymbol{\mathcal{G}}(q) = [\mathcal{G}_1(q), \cdots, \mathcal{G}_N(q)]^T$ collects the MIMO models around the considered operating points, then the predicted output of *PMnet* is:

$$\hat{\boldsymbol{y}}[n] = \boldsymbol{\omega}^T \boldsymbol{\mathcal{G}}(q) \boldsymbol{u}[n], \tag{9}$$

which exhibits a non-linear behavior with respect to $\boldsymbol{u}[n]$.

B. Application to power converters

To model power converters using *PMnet*, the first step is to define the inputs $\boldsymbol{u}[n]$ and outputs $\boldsymbol{y}[n]$ of the multi-ports system, as well as the input space $\mathcal{U} \in \mathcal{R}^{n_u}$, which determines the range of possible input values. The method identifies 2^{n_u} submodels following an orthotope-based partition of $\mathcal{U}$. For every submodels $\mathcal{G}_k(q),\ k = 1, \cdots, N$, the input-output relations $G_{ij}(q),\ i = 1, \cdots, n_y,\ j = 1, \cdots, n_u$ are identified for every input-output pair. The input-output relations $G_{ij}(q)$ are ARMAX models, and time-domain data are gathered for their identification by exciting one input at a time using pseudo-random binary signals (PRBS), which provide a sufficiently broad frequency spectrum for accurate linear model identification [9]. The vector of submodels $\mathcal{G}(q)$ is encapsulated in a neural network using a *dynoNet* structure [10] along with the neural network-based weighting function modeled as a multi-layer perceptron (MLP), as shown in Fig. 1. Even though more sophisticated machine learning methods exist, using a simple MLP in combination with linear models provides the advantages of interpretability and minimal computational burden. Once the neural network is trained over a large dataset containing the converter's dynamics over its entire operating space, the method proposes new submodels to be identified based on the analysis of the MLP.

To obtain the necessary data for the submodel identification and the training of the neural network-based weighting function, precise measurement devices are necessary to ensure a sufficient signal-to-noise ratio. Often, these requirements cannot be fulfilled in laboratories. C-HIL simulation is a viable option as it allows easy testing while being very close to reality. The next section outlines the various benefits of C-HIL simulations.

III. Data acquisition on a C-HIL DC-DC converter digital twin

Although the methodology is applicable to any type of power electronics converter we focus on its application to an industrial DC-DC converter. The first reason is the relative simplicity of the DC-DC PECs, which allows us to be more confident in the analysis of our results. The other reason is that a detailed description of a commercial PEC in a C-HIL may be more informative for potential users.

In this section, we first provide our motivations for using C-HIL for model identification. This is followed by a detailed description of the implementation using a DC-DC converter.

A. C-HIL motivation

Several categories of HIL simulation have emerged over time [11]. The one used for this paper is C-HIL which interfaces the hardware of control with a real-time digital simulator. The plant of the system is therefore contained in the real-time digital simulator compared to other categories such as Power-HIL (P-HIL). In P-HIL, part of the plant can be outside the simulator as hardware but still interface with it [11].

The tool used for this paper is a C-HIL platform developed by Typhoon HIL Inc. [12], specialized for the simulation of power electronics and power systems in general. Since the first version [13], the tools have been used in many applications. For instance, C-HIL has shown their utility and benefits in [14] and [15], by helping to tune the parameters of a new controller for STATCOM, or by validating the architecture of a grid resynchronization algorithm for grid forming inverters. The fidelity of the C-HIL simulation compared to a complete hardware system has been studied and confirmed in [16]. This is a first motivation to use C-HIL in our approach. The second

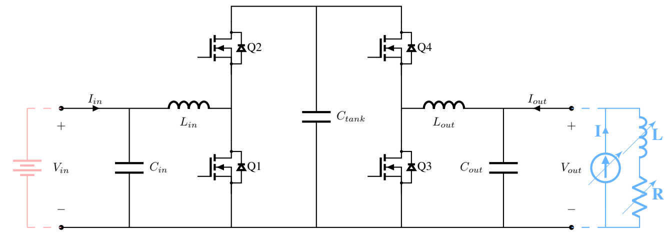

Fig. 2. DC-DC converter topology to model for C-HIL simulation. Pink and blue components are added for the tests described in section IV

is related to the ability to preserve manufacturers data privacy as described in the following subsection.

B. Power converter twin model description

To test the proposed method, an industrial DC-DC PEC is chosen. In this way, the results can be compared with measurements of a physical system considered as a reference to be approached.

The PEC has two ports, and it is bidirectional, which means that the power can flow in both directions. For convenience, in the rest of the paper, one port is named the input port (In) and the other the output port (Out). The DC-DC converter has been designed to regulate a power transfer in order to balance each port voltage around 380 V. The basic idea is that if the voltage is greater on the input port than on the output one, the power should flow from the input toward the output and inversely. This behavior is designed for DC microgrid applications where some bus voltages have to be regulated to stay close to a specified nominal voltage.

In practice, the condition governing the power transfer is more complex than mentioned before. The user can tune some parameters to specify threshold voltages the control algorithm uses to decide if a port should sink, inject power, or even not exchange power. Indeed these threshold values define three operation ranges for each port: a state where the port will ask power from the other port due to an undervoltage, a state where the port will give power to the other due to overvoltage, and a dead band where the port asks nothing. The resulting power setpoint for the control of the converter is the sum of each independent power need.

Except for this mechanism of power setpoint computation, the rest of the controller is entirely unknown. A C-HIL simulation is, therefore, ideally suited as the manufacturer only has to provide the actual controller board with the associate firmware already loaded on the chip to obtain a digital twin of the converter running in real-time. The control board has to be interfaced correctly with the C-HIL emulator, and most importantly, the emulator has to contain a model of the converter plant. In this case, the model of the converter plant is the true electrical circuit whose topology is represented in Fig. 2.

C. Configuration and data acquisition

The converter is a two-port circuit, thus four variables describe entirely the system behavior: V_{out}, V_{in}, I_{out}, and

I_{in}. A current and a voltage from different ports are chosen as $\boldsymbol{u}[n]$. The outputs $\boldsymbol{y}[n]$ are the remaining ports' voltage and current.

$$\boldsymbol{y}[n] = \begin{pmatrix} I_{in}[n] \\ V_{out}[n] \end{pmatrix} \qquad \boldsymbol{u}[n] = \begin{pmatrix} V_{in}[n] \\ I_{out}[n] \end{pmatrix}$$

This definition of the MIMO system is classic for two-port circuits and corresponds to finding the inverse hybrid parameters of a voltage amplifier. Indeed our DC-DC converter can be seen as a voltage amplifier from one port to another as the control modulates voltage through transistor switching (as illustrated in Fig. 3). The converter's bidirectional characteristic can also match the analogy with the voltage amplifier by considering that the converter is a special voltage amplifier that can decrease or increase the voltage and where either a positive or negative current can flow.

The choice of inputs and outputs allows browsing all operating points which include descriptive dynamics of the system during the data acquisition.

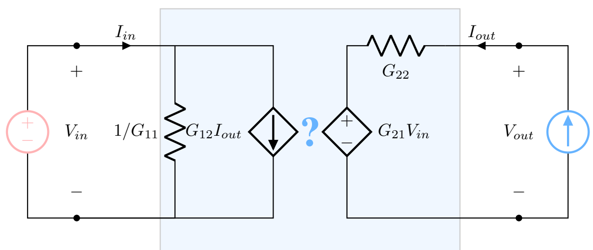

Fig. 3. Two port equivalent representation of the DC-DC converter.

It is important to notice that in practice the converter could be configured with different threshold voltages on each port. These threshold voltages are used by the control algorithm. This implies that the black-box model that we derive in this paper is bound with the chosen set of parameters. For simplicity, the same parameters are imposed on each port to obtain a symmetrical system. However, the designation $_{in}$ and $_{out}$ are still used for reference.

IV. Simulation Conditions and the Results

A. Simulation conditions

To harvest data for the *PMnet* algorithm, controlled current and voltage sources are added in the C-HIL emulator model to be able to excite our inputs $\boldsymbol{u}[n]$ with external PRBS. A python code automates the data acquisition of $\boldsymbol{u}[n]$ and $\boldsymbol{y}[n]$ signals during the C-HIL simulation. It uses API instructions included in the software platform and designed to speed up and facilitate this type of testing that R&D validation teams often have to perform. Voltage and current signals are sampled at 100kHz and the capture lasts 30 seconds for each operating point. PRBS have a maximum frequency of 100Hz to extract slow dynamics that are relevant for system-level studies.

B. Results

Two cases are presented:

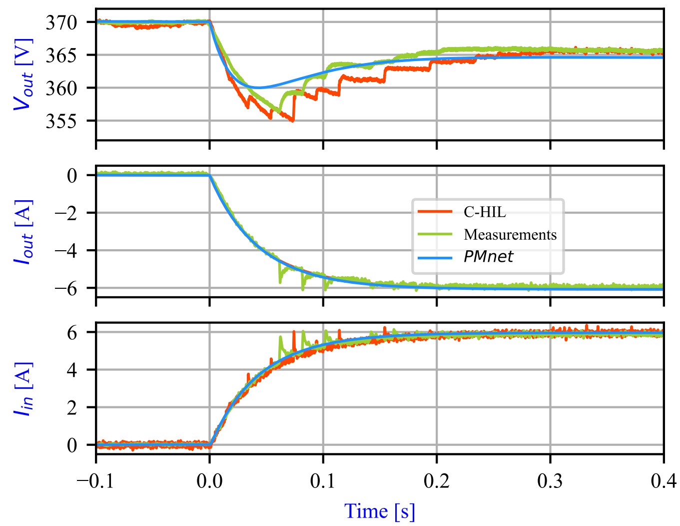

Fig. 4. Comparison between the measurements and two different modeling techniques when the DC-DC converter is connected to *R*-*L* series circuit.

1) a *R*-*L* series load to evaluate the effectiveness of the used modeling approach, and
2) a Small DC system, to assess the proposed methodology for system-level studies.

1) R-L series: We evaluate the effectiveness of our modeling technique by comparing its performance with that of C-HIL modeling and measurements collected during a specific experiment. The converter is supplied with a constant input voltage, and its output port is connected to a *R*-*L* series circuit at time 0s. The output current I_{out} is the response of the *R*-*L* series circuit to a voltage V_{out}.

In Fig. 4, we observe that *PMnet* exhibits a greater voltage *nadir* than in measurements and C-HIL modeling. However, the overall behavior is similar, and the steady-state values are less than one volt apart for output voltage V_{out} and superpose for the input current I_{in}. We also see that *PMnet* is not capable of representing fast transients caused by quick changes in the duty cycle as it is an averaged model. Nevertheless, the primary objective of *PMnet* is rather to describe the general behavior of converters when connected to various system configurations, and not predicting fast transients that are irrelevant for system-level studies.

2) Small DC system: We assess the suitability of *PMnet* for performing system-level studies by comparing its performance to that of the HIL modeling technique on the system of Fig. 2. A lithium-ion battery is on the input side of the DC-DC converter. It is modeled as described in [17]. A variable current source and a variable *R*-*L* series load are connected on the output side.

To demonstrate the efficacy of *PMnet* in system-level studies, we conduct a test wherein we vary the values of three components over time and observe the voltage and current responses. Initially, we consider a simple *R*-*L* series circuit with varying values, followed by setting the inductance to zero to obtain a pure resistance load. Subsequently, we add a current

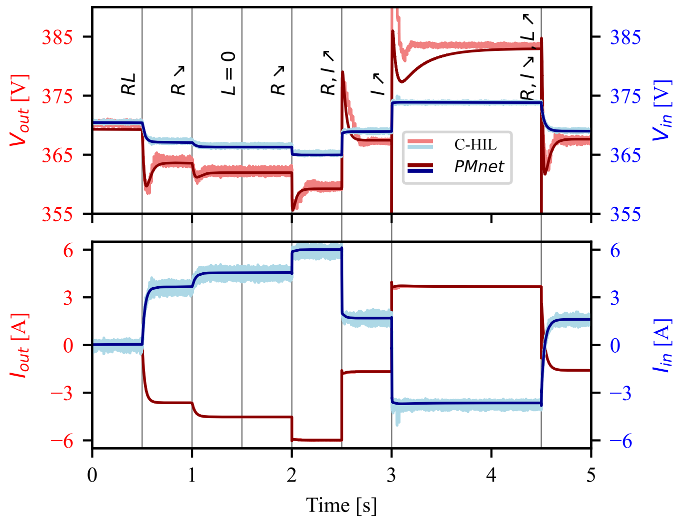

Fig. 5. Comparison between *PMnet* and the C-HIL modeling technique when the DC-DC converter is integrated into a small DC system.

source to reverse the power flow and gauge the reliability of *PMnet* during battery charging. Finally, we reconnect a *R-L* series to demonstrate the power flow reversal, concluding the scenario.

By the analysis of the results of *PMnet* and the comparison with the C-HIL modeling technique (Fig. 5), we found that *PMnet* accurately replicates the results. The only slight discrepancy is observed in the time interval from the fourth and the fifth second, where *PMnet* slightly underestimates the transient rise of the output voltage but eventually reaches the same steady-state value. As for the input current I_{in}, *PMnet* follows the general trend perfectly. Despite not being trained with data from the converter response when connected to a *R-L* series circuit and a battery, *PMnet* accurately describes the general behavior. This indicates that the model performs reliably under different conditions, confirming it as a viable option for system-level studies.

V. Conclusion

Our approach for modeling power converters extends the usage of C-HIL simulations for data harvesting in order to derive black-box models. We draw the following conclusions:

- *PMnet* can accurately represent the dynamic behavior of a converter in various system configurations while maintaining data privacy.
- The modeling technique is highly suitable for simulating complex systems, as it has a low computational burden.
- C-HIL is a viable option for generating the data needed to identify *PMnet* model.

In our future research efforts, we will consider the application of the proposed modeling techniques to other types of power electronics converters (creating a library of models) and its assessment for use in system-level studies using realistically sized systems.

VI. Acknowledgments

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