IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received June 2, 2021, accepted June 18, 2021, date of publication July 5, 2021, date of current version July 16, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3094804

Nonlinear Stability Analysis of DC-DC Power Electronic Systems by Means of Switching Equivalent Models

HESAM MAZAHERI, (Graduate Student Member, IEEE), AIRÁN FRANCÉS, (Member, IEEE), RAFAEL ASENSI, AND JAVIER UCEDA, (Life Fellow, IEEE)
Centro de Electrónica Industrial (CEI), Universidad Politécnica de Madrid, 28040 Madrid, Spain

Corresponding author: Hesam Mazaheri (h.mazaheri@upm.es)

This work was supported by the Spanish Ministry of Economy and Competitiveness through the Project IDENMRED under Grant DPI2016-78644-P.

ABSTRACT The proliferation of renewable energy sources is promoting the use of dc-dc power electronic converters in power distribution systems. It is well-known that the interconnection of power electronic converters can be a source of instabilities. Traditionally, impedance-based stability analyses are performed using either the analytical description or the identification of the output impedance of the source converter and the input admittance of the load converter. However, this methodology is restricted by the small-signal conditions, which are usually violated in this kind of systems due to the high variability imposed by the renewable energy sources. In nonlinear systems, the stability analysis usually consists on the definition of the region of attraction around a stable equilibrium point. In the literature, the analysis of nonlinear systems is almost exclusively applied to analytical systems, where all the details are known. This paper proposes a black-box methodology to obtain the region of attraction of the equilibrium point of commercial off-the-shelf dc-dc converters working in power distribution systems. First, optimization algorithms are used to identify the parameters of a predefined structure, such that it is able to reproduce the dynamic behavior of the system. The parameters identified can be used to create a switching equivalent model that accounts for the nonlinearities produced by the switching process of the converters. Second, the bisection method is implemented to minimize the number of simulations needed to determine the region of stability accurately. The proposed methodology has been validated both with simulations and with an experimental setup.

INDEX TERMS Bisection method, black-box models, digital twin, GAPSO algorithm, nonlinear systems, optimization algorithms, parameters identification, power system dynamics, stability analysis, system identification.

I. INTRODUCTION

Renewable energy resources such as solar, wind, tidal power and biogas have gained a lot of attention in recent years, due to the concerns about the scarcity of conventional fossil fuels resources, environmental degradation, and the increment of the energy demand owing to the population growth [1]–[4].

Microgrids (MGs) have also become very popular as a mean to interconnect distributed energy resources, energy storage systems and loads, forming an autonomous system (Fig. 1). They can be assorted into DC, AC and hybrid MGs. AC MGs are the most popular due to their compatibility with the traditional power distribution system. However, DC MGs have advantages in some applications due to their uncomplicated control, higher efficiency and reliability. Furthermore, they do not require synchronization or frequency regulation in comparison with AC MGs. Nowadays DC MGs are pervasive in many areas such as university campus, malls, industrial applications etc. A hybrid MG takes advantage of both AC and DC power systems and it is recognized as a promising possibility in the near future [5]–[8].

Power Electronic Converters (PECs) play a very important role in MGs. Some of the main reasons are: the need for interfacing AC and DC systems, the interconnection of elements

The associate editor coordinating the review of this manuscript and approving it for publication was Emanuele Crisostomi.

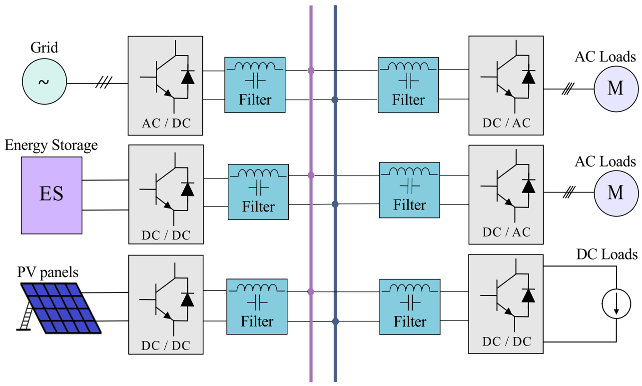

FIGURE 1. DC Microgrid scheme.

with very different dynamic behaviors, the need for controllability, among others [9]. Nevertheless, it is a classical problem that the interconnection of PECs can cause dynamic response degradation or even instabilities in the system. Consequently, it is very important to obtain models able to reproduce the dynamic behavior of these systems and to perform stability analyses.

The modeling and identification process of the nonlinear behavior of power converters can be carried out with various approaches. Amongst distinctive methods, black-box approaches have become popular and deal with the lack of prior information due to the confidentiality issues of the commercial converters. In [10] the identification approach for multiple-input multiple-output systems is carried out characterizing the small-signal dynamic behavior around a particular operating point accurately. The black-box model can be identified from the frequency response of the PEC or in time domain.

The data obtained from each single model at different operating points, can be merged to form a group of local models. As a result, polytopic models are constructed by using these local models with different weighting functions which give rise to a better approximation. The polytopic model can represent the nonlinear phenomena of the PECs and increase the application of the black-box models [11]–[15]. Furthermore, [16] proposed a large-signal black-box model for characterizing nonlinear behavior of DC-AC converters.

More recent, a DC-DC converter has been modeled and identified by training currents and voltages at converter terminals with a Nonlinear AutoRegressive eXogenous Neural Network (NARX NN). In [17] this black-box approach has been capable of reproducing the nonsynchronous buck converter dynamic behavior with unknown configuration.

Parallel with black-box approaches, there are numerous and diverse procedures for system identification considered non-parametric approaches including white-box and gray-box models. Kalman filter approach can be applied for real-time parameters estimation of DC-DC converters with high accuracy and fast convergence rate which provides us with precise coefficients of the transfer function. Compared to conventional approaches such as recursive least square, Kalman filter is mathematically simpler [18], [19].

These approaches have proved to be very useful to reproduce the dynamic response of the PECs, however, the lack of any physical meaning in the identified model is a handicap to perform nonlinear stability analyses. Other approaches assume that some basic information about the PEC topology is known and use it to create a structure with physical meaning.

Reference [20] is associated with the white-box non-linear least square identification aiming at minimizing the error function for nonlinear systems. The trust-region reflective least square solver is employed for solving nonlinear constraints. In this algorithm, in order to optimize the results, a boundary for the parameters of the converter needs to be defined. This approach is applicable not only for identification of DC-DC converters but also for variety of applications such as filters and rectifiers. In [21] the parameters of the buck converter model were identified using a white-box model by obtaining data from the open-loop model and the closed-loop model.

The open-loop parameters identification of the buck converter can be achieved by utilizing Particle Swarm Optimization (PSO) algorithm, applying changes in the load to perturb the system. The method needs prior information about mathematical models and dynamic behaviors of the converter. In the identification process, the cost function minimizes the sampling data coming from the output voltage and inductor current. Moreover, the fourth order Runge-Kutta method is employed to linearize the mathematical model of the studied buck converter [22].

Previous research showed the importance of system identification in MGs. Another fundamental research is the stability analysis of these systems. Stability analysis of power converters can be classified as small-signal and large-signal and for this reason, linear and nonlinear approaches can be applied.

The application of the Black-Box Terminal Characterization model (BBTC) can be extended to analyze the small-signal stability by measuring input/output impedance criterion of Middlebrook [23]. In the Middlebrook's criterion the stability is not only assured but also there is no dynamic coupling between different converters. Despite these strength points, it is a very restrictive method and it is also restricted for linear systems.

A typical nonlinear phenomena that affects the stability of power electronic systems is the presence of Constant Power Loads (CPL). When it comes to analyze the stability of this system, not only the behavior of the CPL, but also the dynamic interaction between the source converter and the load converter are considered instability sources and detailed examination is needed [24].

A study based on the Floquet theory for the stability determination of periodic motions of the cascaded converters system is carried out in [25]. The Floquet theory can be applied to the class of linear differential equations. In comparison with the Middlebrook's criterion, Floquet theory is more accurate, however, it requires more information.

Large-signal stability approaches, such as Lyapunov-based methods, have significant importance in systems where the small-signal condition is not complied with. However, Lyapunov stability theorem can state if a system is stable, but cannot provide any information about the instability of a system. Moreover, detailed prior information about the state equations of the system is needed, whereas, for Middlebrook's criterion, input and output impedances are sufficient to check the stability. As a result, the Lyapunov-based approach for checking the large-signal stability may be considered less feasible for the black-box models.

To the best of the authors knowledge, in the literature none of the system identification methods for PECs have been applied for large-signal stability analysis. Due to the lack of a practical solution for the nonlinear stability analysis of systems based on commercial PECs, this paper proposes a novel approach based on switching equivalent models. Assuming that some basic knowledge about the PECs is available, which is usually included in their datasheets, the idea is to use optimization algorithms to identify the parameters of the converter and its control loop. With this information it is possible to create a switching model with the same dynamic behavior, which has information about the nonlinear behavior due to the switching process of the PEC. Finally, the switching equivalent model is used to find the Region of Asymptotic Stability (RAS) around any operating point. The bisection method is used to minimize the number of iterations needed to define the RAS.

Some strong advantages of this identified model are that it includes the nonlinearities due to the switching process and it also maintains some physical insight about the converter. These characteristics allow to obtain the nonlinear state-space equations and to interpret the results in terms of state variables. With this information, any of the large-signal stability analyses proposed in the literature can be implemented without the need of having all the details about its design. Besides, it is also possible to perform extensive simulations to account for any possible scenario in the dc microgrid. Finally, it would be possible to create a digital twin [26] of the PECs and the dc microgrids using the proposed methodology as discussed in the future work.

The rest of this paper is structured as follows. Section II describes the use case involving a CPL. Section III describes the optimization algorithm along with its advantages and drawbacks. System identification in open loop and closed loop besides the results are described in Section IV. Experimental verification is presented in Section V. In Section VI the stability analysis obtained from a numerical method is determined and, finally, Section VII is dedicated to conclusions and future work.

II. SYSTEM OVERVIEW

A typical source of instability in power electronic systems is the existence of tightly controlled load converters. These converters demand a very constant power from the source converter and consequently, from their input ports, they behave as a negative resistor, which value depends on the power demanded by the load. This nonlinear stability problem can be usually seen in the cascaded connection of PECs. This system will be used as case study to present the proposed methodology. In this section the system is described.

The parameters of the cascaded buck converter can be identified by means of optimization methods. For this purpose, an appropriate input and output should be chosen. Previous studies in black-box model identification have emphasized the fact that as a result of considering the system a black-box model, for DC-DC power converters the currents and the voltages inside the black-box model are neither allowed to be measured and used nor are accessible. Therefore, the variables that can be accessed are the following:

- Output resistance.
- Input voltage.
- Reference voltage of the controller in closed-loop system.
- Duty-cycle in open-loop system.

The studied system is a cascaded buck converter with the load converter regulated by proportional-integrate controller showed in Fig. 2 with the following dynamic equations (1):

$$
\begin{aligned}
\dot{x_1} &= \frac{d_1 V_{in1} - (R_{L_1} + R_{C_1})x_1 - x_2 + d_2 R_{C1} x_3}{L_1} \\
\dot{x_2} &= \frac{x_1 - d_2 x_3}{C_1} \\
\dot{x_3} &= \frac{d_2 x_2 + (d_2 x_1 - d_2^2 x_3) R_{C_1} - (R_{L_2} + R_{C_2}) x_3 - x_4 + (\frac{R_{C_2} K}{R_{C_2} + R_o})}{L_2} \\
\dot{x_4} &= \frac{x_3 - (\frac{1}{R_{C_2} + R_o})K}{C_2} \\
\dot{x_5} &= K_i (V_{ref} - (\frac{R_o}{R_{C_2} + R_o})K) \\
d_2 &= SAT_0^1 (K_p (V_{ref} - (\frac{R_o}{R_{C_2} + R_o})K + x_5) \\
K &= x_4 + R_{C_2} x_3, \qquad (1)
\end{aligned}
$$

where C, L, R_C and R_L correspond to the capacitor, inductor, equivalent series resistance of the capacitor (ESR) and winding resistance of the inductor respectively. V_{in1} represents the input voltage. V_{ref}, K_p and K_i correspond to reference voltage of controller together with coefficients of proportional-integral controller. d_1 as well as d_2 denote duty

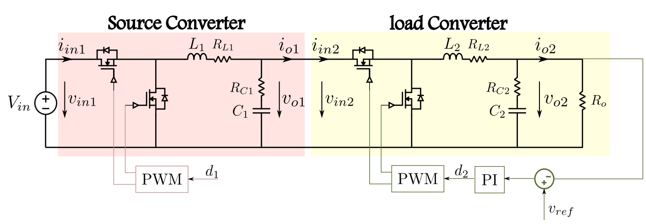

FIGURE 2. Cascaded buck converter model.

cycles of the converters and saturation function of the controller is symbolized as SAT. Indices 1 and 2 designate the primary converter as a source converter and secondary converter as a load converter. Finally, the vector x_i stands for state variables, where x_1 and x_2 represent the inductor current and the capacitor voltage of the primary converter, x_3 and x_4 correspond to the inductor current and the capacitor voltage of the load converter, and x_5 defines the product of the integral coefficient of the PI controller and the error signal.

Since the system is composed of energy storage elements and also due to the fact that capacitor and inductor in the series connection generates a natural frequency, so as to achieve accurate parameters identification, the dynamic model of the buck converter is required to be stimulated somehow in order to show its natural frequency. Amongst different kind of signals for system identification, the square-wave signal is considered one of the best. As this signal contains a wide range of harmonics in frequency domain, which depends on the slew rate, it can be applied for converter identification. The point that should be taken into consideration is that, for an identification, the system should not be damaged and it is allowable to obtain the parameters of the model only by applying a signal and measuring the voltage or the current. One of the strength points of the proposed method is that only by employing output signal waveform of the resistor R_o, the parameters can be estimated.

III. OPTIMIZATION ALGORITHM

The proposed methodology involves the use of optimization algorithms to identify the parameters of the converters that reproduce the dynamic response of the PECs. In this section, the advantages and limitations of two nature-inspired algorithms are briefly described. The algorithms considered are PSO and Genetic Algorithm (GA). Finally, a combination of both, hybrid GAPSO algorithm, is implemented to exploit their advantages.

A. GENETIC ALGORITHM

GA is one of the effective optimization technique for complex optimizations. This technique can be utilized for solving problems based on natural evolution and will find optimal solution after a number of successive generations [27]. In general, the optimization of problems without a mathematical function as an objective function, is difficult. In this study, the objective function is obtained from the comparison of the model response with the PEC response. Although GA has its advantages such as supporting multi-objective optimization problems and the capability of not being trapped in local optimal solution, the reason why GA may not perform individually for parameters identification in this kind of problems, can be expressed briefly as low convergence rate which is a time-consuming process [28].

B. PARTICLE SWARM OPTIMIZATION ALGORITHM

This algorithm is inspired by the response of social organisms in groups, such as bird and fish schooling. PSO emulates the interaction between members to share information [29], [30]. Compared to GA, in PSO a population of individuals (swarm) is preferred rather than concentrating on a single individual implementation. Then, the algorithm instead of moving a single individual around, will move the population around and looking for a potential solution. This is an example of a heuristic approach, where there is no guarantee of an optimal solution. This technique based on the swarm intelligence, will look for optimum points and because of this it has a high convergence speed to reach around the global optimum point. Despite having strength points such as easy implementation and simplicity, this method does not perform well in more complex problems [31].

C. HYBRID GAPSO ALGORITHM

The pros and cons of PSO and GA have been described. Due to the drawbacks of the mentioned evolutionary algorithms in solving optimization problems, a combination of PSO and GA has been selected, so as to benefit from the advantages of both. The PSO algorithm helps to approach the proximity of the global minima with a low computational effort, whereas the GA helps to avoid local minima and to obtain the global minima accurately [32]. The advantages of the GAPSO algorithm have been used in some other applications [33], [34]. In this work, it is proposed to use the hybrid GAPSO algorithm for the identification of the parameters that describe the nonlinear dynamic behavior of power electronic converters.

IV. SYSTEM IDENTIFICATION

The identification of the two-stage cascaded buck converter has been divided into two parts: the open-loop and the closed-loop systems. From the open-loop system identification, the values of the parameters C, L, R_C and R_L will be obtained and then, from the closed-loop system identification test, the values of the coefficients of the Proportional-Integral (PI) controller will be identified.

A. OPEN-LOOP PARAMETERS IDENTIFICATION

The identification of the open-loop parameters will be presented using two possible perturbations: variations in the output resistance and variations in the duty cycle.

1) VARIATIONS IN THE OUTPUT RESISTANCE

In (1) the state-space equations of the model shown in Fig. 2 were presented. It has been described in the previous section that to avoid damaging the system, for system identification, appropriate inputs are needed. In this part, the variations of the output resistor R_o have been selected as an input for identification. By changing R_o, the output current and the equilibrium points of the system will be altered. It should be taken into account that the changing rate of the output resistor should be slower than the dynamic behavior of the system as to be able to represent the oscillations of the system in the output. Attention should be paid to the changing time, so it is not to be too high, owing to the fact that in optimization

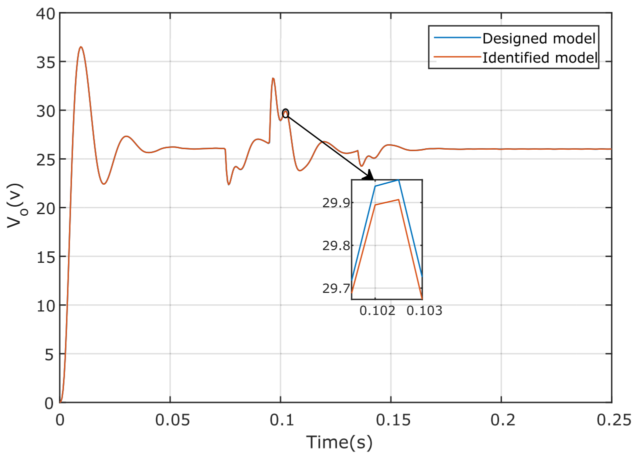

FIGURE 3. Output voltage comparison between designed and identified models in the open-loop test with variations of R_o.

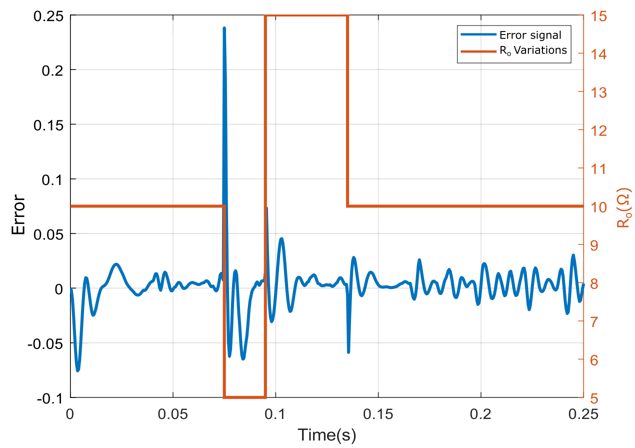

FIGURE 4. Variations of R_o and the error signal.

algorithm the oscillations will be disregarded and it will focus on minimizing the final error.

By applying the changes on the output resistance, it is expected that the output voltage changes substantially and based on these changes, the values of the parameters of the open-loop system can be identified. It is a notable point that the system parameters will be identified just by changes of R_o and observing the behavior of the output voltage V_{o2} of the load converter, which can be easily reproduced experimentally.

Choosing proper objective functions is one of the most important parts in optimization problems. The function candidate here is the Root Mean Square Error (RMSE).

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N} Error(n)^2} \tag{2}$$

where *Error* represents the difference between actual values and predicted values and N denotes the number of observations. The initial values of the parameters of L_1, L_2, C_1, C_2, R_{C_1}, R_{C_2}, R_{L_1} and R_{L_2} have been considered as zero in the open loop optimizer program.

The comparison between the output voltage of the identified model and the designed one is depicted in the Fig. 3. At the beginning, all the initial conditions of the system are equal to zero and the dynamic response shows a particular resonance frequency. Afterwards, the changes in the output resistor generate a different resonant behavior. Two LC filters and their corresponding inherent frequencies of the cascaded buck converter generate this waveform, which has a significant importance for the identification of the parameters of the primary converter of the model.

It is noticeable that the identified values are quite similar to the designed values and the error signal together with R_o variations can be seen in Fig. 4. Another flexible input variable such as the duty-cycle is studied as an input.

2) VARIATIONS IN THE DUTY-CYCLE

In this section, R_o is considered constant. In this case, the changes will be performed in the duty-cycle of the secondary converter, keeping the duty-cycle of the first converter constant. Then, the parameters of the system will be identified by analyzing the output voltage dynamic response. Equivalently to the case of the identification process using the output resistor, the initial values are considered as zero. As it can be seen, the identified output voltage waveform is quite similar to the designed one and this illustrates the accuracy of the proposed model (Fig. 5). The error signal and the duty-cycle changes are represented in Fig. 6.

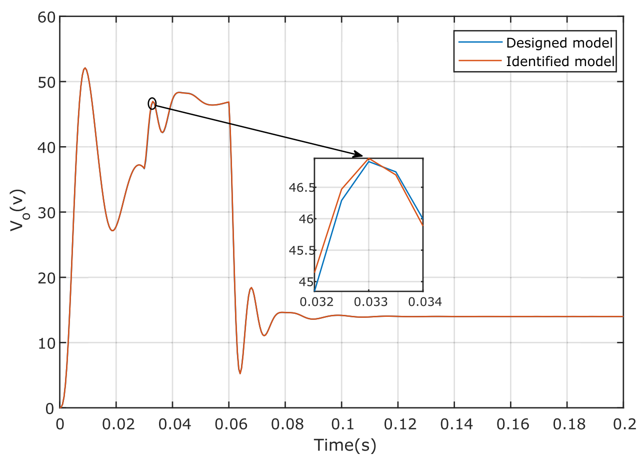

FIGURE 5. Output voltage comparison between designed and identified models in the open-loop test with variations of the duty-cycle d_2.

From the two mentioned approaches for the open-loop model identification, it can be concluded that both methods (changing output resistance and duty-cycle) can identify the parameters of the system accurately. However, in the cases where the duty-cycle is available, it is usually preferred due to its simple implementation.

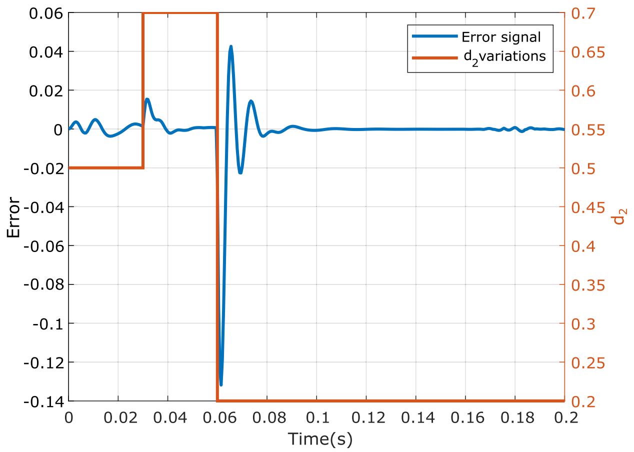

FIGURE 6. **Variations of the duty-cycle of the secondary buck converter and the error signal.**

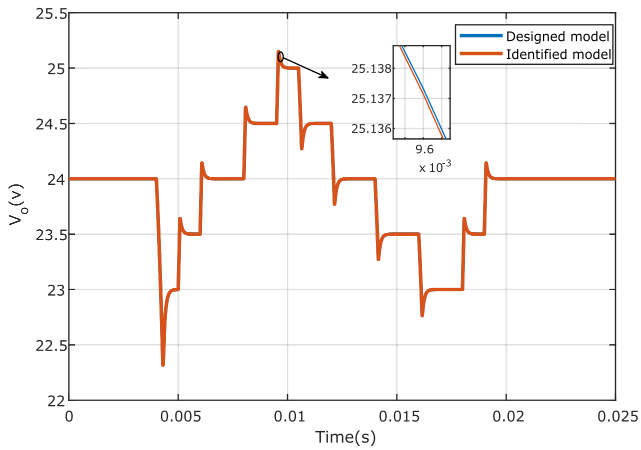

FIGURE 7. **Output voltage comparison between designed and identified model in closed-loop test with variations of the reference voltage.**

TABLE 1. **GAPSO Parameters.**

Maximum Number of Iterations	100
Maximum Number of Sub Iterations for Genetic Algorithm	5
Maximum Number of Sub Iterations for PSO Algorithm	10
Swarm Population size	50

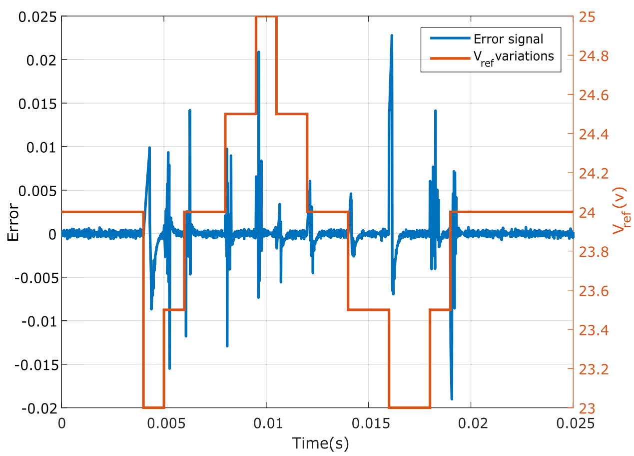

FIGURE 8. **Variations of V_{ref} and the error signal.**

B. CLOSED-LOOP PARAMETERS IDENTIFICATION

A PI controller has been employed for the load side converter. Generally, the coefficients of the PI controller are chosen in a way so as to achieve the best performance of the system. The purpose of this study is the identification of the closed-loop system and subsequently obtaining the domain of the attraction. For this reason, specific controller coefficients have been used such that the stability region exists (see Table 2).

Similarly to the open-loop identification, as the internal components of the converter cannot be accessed, appropriate input should be picked. The output voltage, V_o, will be utilized for data sampling and the comparison of the output voltage of the designed model and the identified model is shown in Fig. 7. A proper accessible input in this identification process, considering the system as a black-box model, is the reference voltage. To have an exact identification, this mentioned input signal is required to be perturbed properly. The variations of the reference voltage are around its equilibrium point of 24 V.

A system is identifiable while it works in its stable mode and on the contrary, it will be difficult or even impossible to be identified when it turns to its unstable mode. As a consequence, the input signal has been considered with a variation of one volt around the stability region. Fig. 8 represents the reference voltage variations, V_{ref}, as well as the error signal.

Since the system has two unknown parameters, it is possible to draw the three-dimensional plot of the RMSE so as to represent graphically the complexity of the identification of the parameters in relation to the parameter values of the controller. A small area around the objective has been regarded, with the steps of 0.1 for K_p and K_i. As it can be seen in Fig. 9, there are plenty of the extremum points and finding the global optimum point is not a simple task. Consequently, the optimization algorithm of GAPSO with the following specification is exercised in Table 1 for system identification in open-loop model and closed-loop model.

1) CHOOSING INITIAL VALUES OF STATE VARIABLES IN A CLOSED-LOOP SYSTEM MODEL

Initial values in the closed-loop system model are important. It is worth noticing that in nonlinear systems, the stability of the system depends on the initial conditions of the state variables. Therefore, the system that is going to be identified should stay in its stability region and this can be done by choosing appropriate initial values for state variables. Furthermore, the variations of the reference voltage have been restricted to a small region close to the area in which the system works in its stable mode. However, the initial values of the state variables are still unknown.

An important point here is that if there is a controller that can make the system stable, regardless of the values of

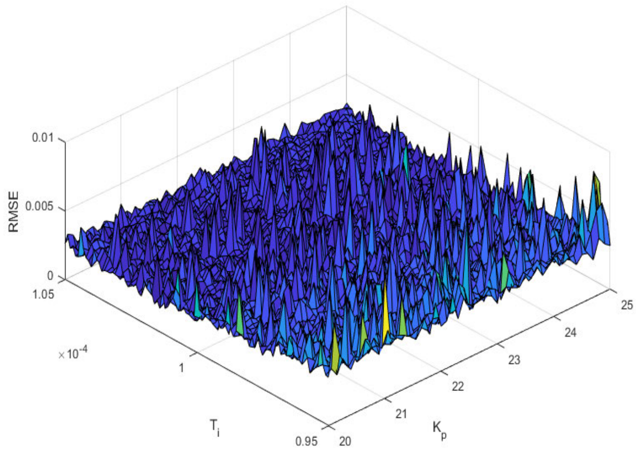

FIGURE 9. RMSE for parameters of the PI controller.

its coefficients, in the end the state variables will reach the unique equilibrium points. By using this principle, the coefficients of the controller have been chosen randomly in a way that the system does not go to its unstable mode. Afterwards, by solving the state equations and calculating the vector of the values of the equilibrium points of the system, proper initial values equal to initial values of the black-box model are achieved.

In Table 2 the parameters of the designed model are indicated as *Designed*. Method 1 refers to the data obtained perturbing the model in open-loop using the duty cycle, whereas Method 2 refers to the data obtained in the closed-loop model. The abbreviations OL and CL are associated with open-loop and closed-loop model, respectively. The small difference between identified values and designed values, represents the suitable performance of the GAPSO algorithm. Then, by substituting these values into the dynamic equations of the system (1), the output voltage V_o can be obtained.

TABLE 2. Identified parameters values.

	Designed	*Method* 1	*Method* 2
$L_1(mH)$	13	12.968	13.057
$C_1(\mu F)$	560	561.198 F	557.284
$R_{L_1}(\Omega)$	1	0.983	1.001
$L_2(mH)$	5	4.994	5.011
$C_2(\mu F)$	330	331.357	329.541
$R_{L_2}(\Omega)$	0.25	0.258	0.249
$R_{C_1}(\Omega)$	0.95	0.972	0.956
$R_{C_2}(\Omega)$	0.87	0.874	0.865
$d_1(OL)$	0.9	0.5	0.9
$d_1(CL)$	0.9	0.9	0.9
$d_2(OL)$	0.35	0.7	Variable
$d_2(CL)$	Variable	Variable	Variable
$R_o(\Omega)$	10	Variable	10
$V_{in1}(V)$	80 (constant)	80 (constant)	80 (constant)
V_{ref}	24	24	Variable
K_p	23.8787	23.0748	22.5469
$T_i(\mu s)$	101.129	100.614	99.918
$K_i = \frac{K_p}{T_i}$	236121.19	229338.86	225653.97

V. EXPERIMENTAL VERIFICATION

In this section, the same procedure will be used for the identification of a real buck converter. The control has an inner current loop and an outer voltage loop. A Dspace Scalexio unit has been used to implement the control, which integrates an FPGA able to generate the PWM signal (10 kHz) and the inner control loop. The outer control loop is implemented in the processor part, which can be modified in real-time using the control desk, Fig. 10.

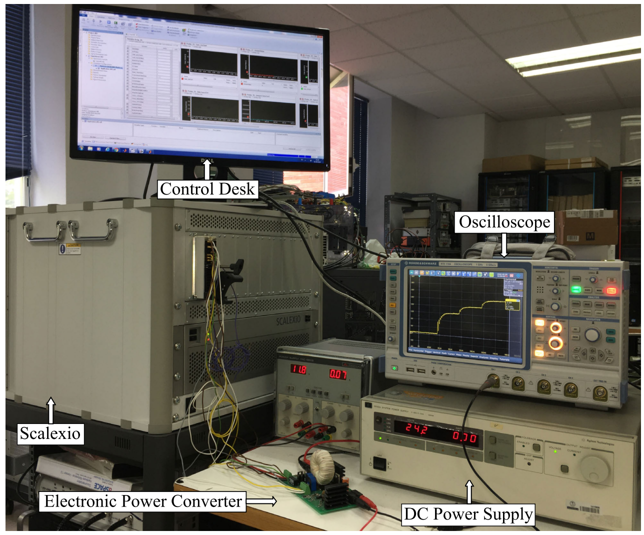

FIGURE 10. Experimental setup.

The experimental tests will be carried out as detailed in Section IV. Perturbing the system while working in open-loop it will be identified the parameters of the inductor, capacitor, the equivalent series resistance of the capacitor and the winding resistance of the inductor, whereas by perturbing the system in closed-loop, the coefficients of the controller will be obtained.

It is worth mentioning that in the identified model the switches are ideal. However, in the practical circuit there are real non-ideal switches which have internal resistances, stray capacitances or inductors [35]. Regarding this, the time period between on and off as well as off and on is significant and can adversely affect the system identification. Besides that, the noise of the sampling system in the measurement process is another factor that can negatively impact making the identification error bigger. It should be emphasized that the values of the parameters of the open-loop model due to the real non-ideal phenomena may be different from their theoretical values. The identified system in this case, is the result of all differences and additional parts of the real converter compared to the dynamic equations of the defined system.

A. INITIAL VALUES OF THE STATE VARIABLES

In commercial PECs it is not possible to have access to the initial values of the inductor currents and capacitor voltages. To solve this issue, the duty-cycle is considered constant for a certain period of time, 0.2 in this example. Hereby, the system from whatever initial values, which we have no prior information, will reach the specific values of this operating point in steady state. If the system has been identified accurately,

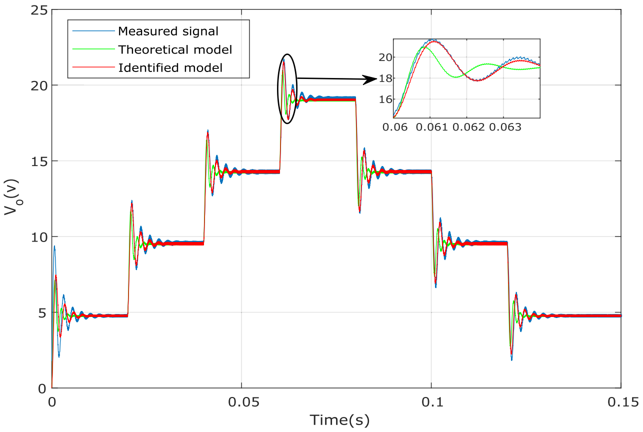

FIGURE 11. **Output voltage comparison between the measured signal and the theoretical and identified models in the open-loop test with variations of the duty-cycle.**

the output voltage waveform must get to the same values at 0.02 seconds. As a result, the data after that specific time, and the sampling data before this time, are eliminated from the experimental system and will be put aside in the system identification. The values between the time zero and 0.02 s are only used for assimilating the initial values of the state variables. Notice that, as shown in Fig. 12, the duty cycle is varied in a wide range within its limits. This particular initial value is completely random and its selection does not affect the identification process.

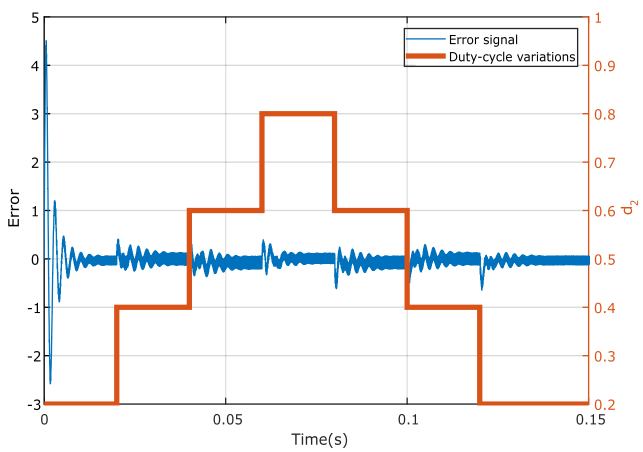

FIGURE 12. **Variations of the duty-cycle and the error signal.**

B. PARAMETER IDENTIFICATION OF THE OPEN-LOOP MODEL FOR THE BUCK CONVERTER

It can be concluded from the previous sections that, variations of the duty-cycle are not only more efficient but also safer than changing the output resistance of the system and can be utilized in open-loop system identification. In Fig. 11, the output voltages of the actual converter are compared with the identified model and the theoretical model. The theoretical model has been designed using the expected parameters,

TABLE 3. **Experimental Parameters values.**

	Theoretical parameters	*Identified parameters*
$L(\mu H)$	150	448.4486
$C(\mu F)$	470	299.045
$R_L(\Omega)$	0.15	0.101
$R_C(\Omega)$	0.059	0.265
$R_o(\Omega)$	20 (constant)	20 (constant)
$V_{in}(V)$	24 (constant)	24 (constant)
K_p	0.01	0.011
$T_i(ms)$	1	1.09
$K_i = \frac{K_p}{T_i}$	10	10.842

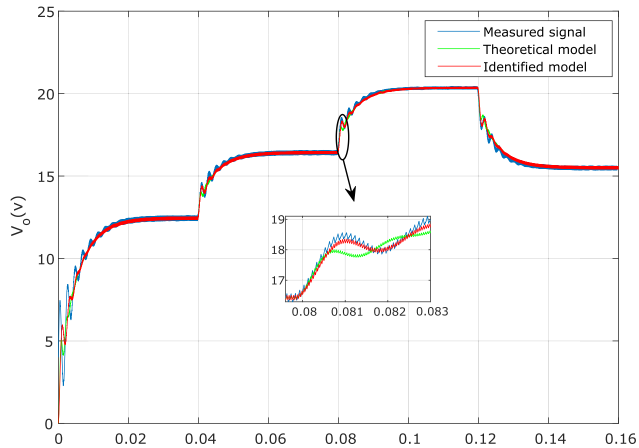

FIGURE 13. **Output voltage comparison between the measured signal and the theoretical and identified models in the closed-loop test with variations of the reference voltage.**

which could be found in the data-sheets of the different elements that integrate the converter.

In Table 3 it can be seen that there is a significant difference between the identified values and theoretical values. The root cause of this is linked with the existence of the integrated circuits (ICs), the driver of the ICs, non-ideal switches, leakage current together with nonlinear behavior of the capacitors and the inductor, among others. However, the identified values reproduce the real dynamic response with a higher accuracy and, consequently, they will provide a better estimation of the RAS.

Variations of the duty-cycle together with the error signal of the identified model for the open-loop test are shown in Fig. 12. Due to having the average part in the formula of the RMSE for the objective function, the optimization method uses the averaged error for the comparison, which reduces substantially the computational burden of the algorithm.

C. PARAMETER IDENTIFICATION OF THE CLOSED-LOOP MODEL FOR THE BUCK CONVERTER

Changes of the reference voltage will be used for closed-loop identification. By choosing this parameter, no damage will be applied to the real system. The reference voltage changes applied are presented in Fig. 14. In this case, the identified values of the coefficients of the controller are very similar to the theoretical ones. This is because of the fact that the

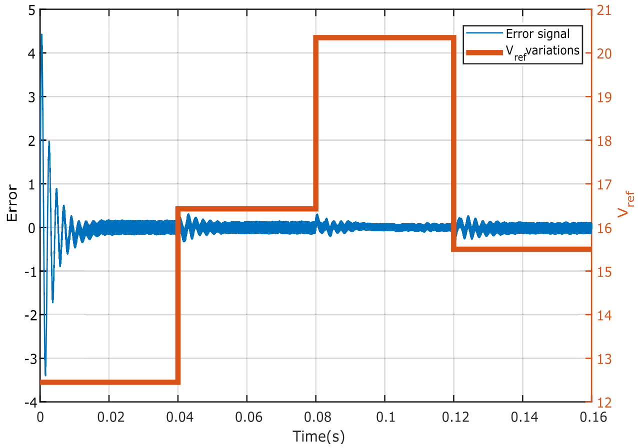

FIGURE 14. Variation of the reference voltage and the error signal.

control loop in the experimental setup is performed using Dspace Scalexio hardware, which receives the measured data from the converter, simulates in real time the controller response, and provides a duty cycle back to the converter. As the controller is implemented in MATLAB Simulink, the theoretical controller formula and the one implemented in the hardware-in-the-loop device of the experimental setup are both the same and the agreement in the identification is very high. Moreover, as with the open-loop identification, the sampling data before the time 0.035 seconds has not been used in the optimizer program and the desired output is considered after the first settling time of the system. The comparison among the identified and the theoretical model with the experimental result is shown in Fig. 13, and the difference between the identified model and experimental model is shown in Fig. 14. At the beginning, it can be seen that the error is big, which comes from not having the same initial values. The parameters of the buck converters including the PI controller coefficients are shown in the Table 3.

VI. STABILITY ANALYSIS

A. STABILITY ANALYSIS BY SIMULATION

Gridding the coordinate plane and simulation of the different sampling points for a system is the prime idea that springs to mind with respect to stability analysis. The accuracy and precision of this method depends on the number of sampling points simulated. It is clear that a lower distance between the sampling points brings about a higher accuracy of the basin of attraction. On the other hand, the question which comes to mind is that how small this distance could be. It should be taken into consideration that there is a trade-off between the accuracy and exactness of the determined stability region and the duration of the process of searching for this region. Due to the fact that the simulation is a time consuming process, it is necessary to use a methodology to avoid the simulation of all the sampling points and obtaining and plotting the exact region of the stability only by the simulation of some specific points.

B. STABILITY ANALYSIS BY BISECTION METHOD ALGORITHM

In mathematics, the bisection method is employed to obtain the roots of any given continuous function. To put this in perspective, compared to the direct numerical approaches, this method carries out using an ordered procedure so as to remove redundant and needless computations [36]. In this study, this method has been used for finding the border of the region of the stability. To the best of our knowledge, this approach has not been applied for the analysis of large-signal stability of PECs.

In this algorithm, instead of utilizing the Cartesian coordinates system, the radius, R, and the angle, θ, of the Polar coordinate system have been employed. For the angles of $\theta = \theta_i$, the radius of R will be obtained by the algorithm 2. The choice of n for calculation of θ_i in the algorithm 1 is a trade-off between accuracy and computational burden.

Algorithm 1 θ_i Calculation

```
for i ← 0 to n-1 do
    θ_i = 2πi/n
    Find R_i with algorithm 2
end for
```

Algorithm 2 Bisection Algorithm

```
Consider starting points of a ← 0 & b ← 100
Average the points c = (a+b)/2
Simulate the model for the points a, b and c.
if R = a & R = c are stable and for R = b is unstable
then
    a ← c
    if R = a is stable and R = b & R = c are unstable
    then
        b ← c
        Repeat steps 2 to 7, till |c_new − c_old| ≺ ε
    end if
end if
End
```

In algorithm 2, values a and b are considered such that the system is stable for $R = a$ and unstable for $R = b$. It can be said that the determined region of the stability is the exact possible region of the stability. The advantage of the bisection method in comparison with the previous method is that this method will search for a closed region objectively. The region of stability for the cascaded converters (Fig. 2) is represented in Fig. 15 in which, $n = 40$ of the algorithm 1 has been used. This large-signal stability analysis is based on the variations of two variables: the current of the inductor, I_L, and the voltage of the capacitor, V_C, of the load converter.

In Fig. 16 two trajectories of the capacitor voltage and the inductor current of the load converter are depicted. One corresponds to a stable point, whereas the other corresponds to an unstable point very close to the border of the RAS.

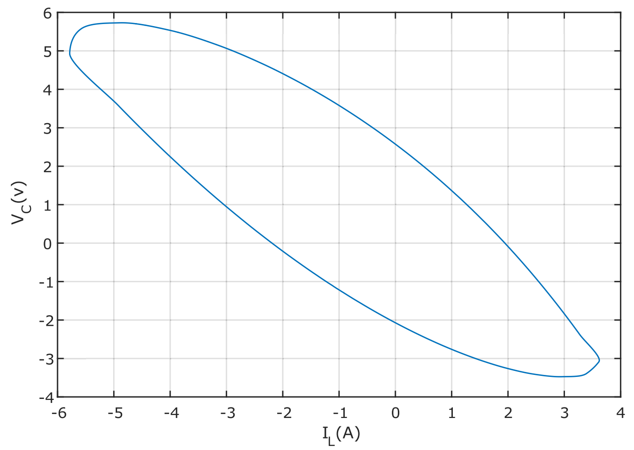

FIGURE 15. Region of asymptotic stability with variations of I_L and V_C of the load converter.

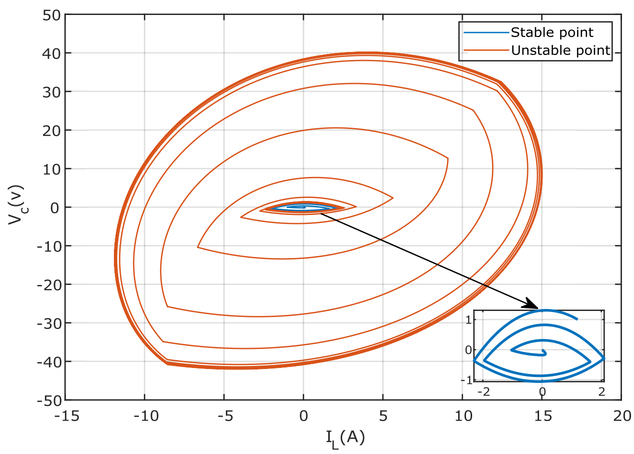

FIGURE 16. Trajectory of I_L and V_C of the load converter for a stable initial condition (1,1) and an unstable initial condition (1.3,1) for the designed model.

In both Fig. 15 and Fig. 16 the state variables are shifted from the equilibrium point of the model ($I_L = 2.4$ A, $V_c = 24$' V) to the origin.

VII. CONCLUSION

The stability analysis of nonlinear systems is a complex task. In the literature, the solutions for power electronic systems are either based on the small-signal approach, such as the impedance-based methods, or in a very precise knowledge about the nonlinear state space equations of the systems. However, in power distribution systems based on power electronic converters, such as microgrids, the operating conditions are very variable and the information about the system is often limited by the manufacturers. This paper proposes a practical approach to simulate and to perform nonlinear stability analysis of power electronic converters with only limited information about their topology. The idea is to use optimization algorithms to identify the parameters of an equivalent switching model, which can reproduce the dynamic behavior of the power electronic converter. A combination of particle swarm optimization and the genetic algorithm is proposed to find the global minima with reduced computational burden. Afterwards, state space equations are extracted from this model and the stability is computed for different initial conditions of the state variables to find the region of attraction around any equilibrium point. The bisection method is used to minimize the number of operations needed to find the region of asymptotic stability. Finally, the method is validated both with simulations where all the details are known and with experimental results.

In the future work, the proposed methodology will be used to create a digital-twin. The model identified can be run in a real-time simulator and the measured data can be periodically sent to the model to continuously update the model parameters by means of the optimization algorithm. Furthermore, both the dynamic information provided by the identified model and the region of attraction obtained can be used to impose limitations in the physical system to avoid malfunction.

REFERENCES

[1] R. Safipour and M. O. Sadegh, "Optimal planning of energy storage systems in microgrids for improvement of operation indices," *Int. J. Renew. Energy Res.*, vol. 8, no. 3, pp. 1483–1498, Sep. 2018.

[2] V. B. K. Gundumalla and S. Eswararao, "Ramp rate control strategy for an islanded dc microgrid with hybrid energy storage system," in *Proc. 4th Int. Conf. Electr. Energy Syst. (ICEES)*, Feb. 2018, pp. 82–87.

[3] T. Dragičević, X. Lu, J. C. Vasquez, and J. M. Guerrero, "DC microgrids—Part I: A review of control strategies and stabilization techniques," *IEEE Trans. Power Electron.*, vol. 31, no. 7, pp. 4876–4891, Jul. 2016.

[4] V. Lavanya and N. S. Kumar, "A review: Control strategies for power quality improvement in microgrid," *Int. J. Renew. Energy Res.*, vol. 8, no. 1, pp. 1–16, Mar. 2018.

[5] T. Dragiv̌ević, L. Meng, F. Blaabjerg, and Y. Li, *Control Power Converters Ac Dc Microgrids*. Atlanta, GA, USA: American Cancer Society, 2019, pp. 1–23.

[6] G. V. B. Kumar and K. Palanisamy, "A review on microgrids with distributed energy resources," in *Proc. Innov. Power Adv. Comput. Technol. (i-PACT)*, vol. 1, Mar. 2019, pp. 1–6.

[7] S. Dahale, A. Das, N. M. Pindoriya, and S. Rajendran, "An overview of DC–DC converter topologies and controls in DC microgrid," in *Proc. 7th Int. Conf. Power Syst. (ICPS)*, Dec. 2017, pp. 410–415.

[8] T. Dragičević, X. Lu, J. C. Vasquez, and J. M. Guerrero, "DC microgrids—Part II: A review of power architectures, applications, and standardization issues," *IEEE Trans. Power Electron.*, vol. 31, no. 5, pp. 3528–3549, May 2016.

[9] A. Francés, R. Asensi, Ó. García, R. Prieto, and J. Uceda, "Modeling electronic power converters in smart DC Microgrids—An overview," *IEEE Trans. Smart Grid*, vol. 9, no. 6, pp. 6274–6287, Nov. 2018.

[10] J.-Y. Choi, B. H. Cho, H. F. VanLandingham, H.-S. Mok, and J.-H. Song, "System identification of power converters based on a black-box approach," *IEEE Trans. Circuits Syst. I, Fundam. Theory Appl.*, vol. 45, no. 11, pp. 1148–1158, Nov. 1998.

[11] L. Arnedo, D. Boroyevich, R. Burgos, and F. Wang, "Polytopic black-box modeling of DC–DC converters," in *Proc. IEEE Power Electron. Spec. Conf.*, Jun. 2008, pp. 1015–1021.

[12] V. Valdivia, A. Barrado, A. Lázaro, P. Zúmel, C. Raga, and C. Fernández, "Simple modeling and identification procedures for," black-box" behavioral modeling of power converters based on transient response analysis," *IEEE Trans. Power Electron.*, vol. 24, no. 12, pp. 2776–2790, 2009.

[13] A. Francés, R. Asensi, O. García, R. Prieto, and J. Uceda, "The performance of polytopic models in smart DC microgrids," in *Proc. IEEE Energy Convers. Congr. Expo. (ECCE)*, Sep. 2016, pp. 1–8.

[14] A. Francés-Roger, A. Anvari-Moghaddam, E. Rodríguez-Díaz, J. C. Vasquez, J. M. Guerrero, and J. Uceda, "Dynamic assessment of COTS converters-based DC integrated power systems in electric ships," *IEEE Trans. Ind. Informat.*, vol. 14, no. 12, pp. 5518–5529, Dec. 2018.

[15] A. Francés, R. Asensi, and J. Uceda, "Blackbox polytopic model with dynamic weighting functions for DC-DC converters," *IEEE Access*, vol. 7, pp. 160263–160273, 2019.

[16] G. Guarderas, A. Francés, R. Asensi, and J. Uceda, "Large-signal black-box behavioral modeling of grid-supporting power converters in AC micro-grids," in *Proc. IEEE 6th Int. Conf. Renew. Energy Res. Appl. (ICRERA)*, Nov. 2017, pp. 153–158.

[17] G. Rojas-Due nas, J. Riba, K. Kahalerras, M. Moreno-Eguilaz, A. Kadechkar, and A. Gomez-Pau, "Black-box modelling of a DC–DC buck converter based on a recurrent neural network," in *Proc. IEEE Int. Conf. Ind. Technol. (ICIT)*, Feb. 2020, pp. 456–461.

[18] M. Ahmeid, P. Missailidis, M. Armstrong, and S. Gadoue, "Parameter estimation of a DC–DC converter using a Kalman filter approach," in *Proc. 7th IET Int. Conf. Power Electron., Mach. Drives (PEMD)*, 2014, pp. 1–6.

[19] M. Ahmeid, M. Armstrong, S. Gadoue, M. Al-Greer, and P. Missailidis, "Real-time parameter estimation of DC–DC converters using a self-tuned Kalman filter," *IEEE Trans. Power Electron.*, vol. 32, no. 7, pp. 5666–5674, Jul. 2017.

[20] G. Rojas-Duenas, J.-R. Riba, and M. Moreno-Eguilaz, "Nonlinear least squares optimization for parametric identification of DC–DC converters," *IEEE Trans. Power Electron.*, vol. 36, no. 1, pp. 654–661, Jan. 2021.

[21] H. Balakrishnan, M. Moreno-Ezuilaz, J.-R. Riba, S. Bogarra, and A. Garcia, "DC–DC buck converter parameter identification based on a white-box approach," in *Proc. IEEE 18th Int. Power Electron. Motion Control Conf. (PEMC)*, Aug. 2018, pp. 242–247.

[22] Y. Peng and H. Wang, "Parameters identification of buck converter based on dynamic characteristics," in *Proc. 10th Int. Conf. Power Electron. ECCE Asia (ICPE ECCE Asia)*, May 2019, pp. 3071–3076.

[23] L. Arnedo, R. Burgos, D. Boroyevich, and F. Wang, "System-level black-box DC-to-DC converter models," in *Proc. Twenty-Fourth Annu. IEEE Appl. Power Electron. Conf. Expo.*, Feb. 2009, pp. 1476–1481.

[24] H. M. Tehrani, A. Frances, R. Asensi, and J. Uceda, "A comparison of stability analysis of constant power load with detailed model in DC microgrids," in *Proc. 7th Int. Conf. Renew. Energy Res. Appl. (ICRERA)*, Oct. 2018, pp. 487–493.

[25] H. Li, J. Shang, X. You, T. Zheng, B. Zhang, and J. Lu, "A novel stability analysis method based on Floquet theory for cascaded DC-DC converters system," in *Proc. IEEE Energy Convers. Congr. Expo. (ECCE)*, Sep. 2015, pp. 2679–2683.

[26] A. Fuller, Z. Fan, C. Day, and C. Barlow, "Digital twin: Enabling technologies, challenges and open research," *IEEE Access*, vol. 8, pp. 108952–108971, 2020.

[27] S. Panda and N. P. Padhy, "Comparison of particle swarm optimization and genetic algorithm for FACTS-based controller design," *Appl. Soft Comput.*, vol. 8, no. 4, pp. 1418–1427, Sep. 2008.

[28] R. Hassan, B. Cohanim, O. de Weck, and G. Venter, "A comparison of particle swarm optimization and the genetic algorithm," in *Proc. 46th AIAA/ASME/ASCE/AHS/ASC Struct., Struct. Dyn. Mater. Conf.*, 2005, p. 1897, doi: 10.2514/6.2005-1897.

[29] D. P. Rini, S. M. Shamsuddin, and S. S. Yuhaniz, "Particle swarm optimization: Technique, system and challenges," *Int. J. Comput. Appl.*, vol. 14, no. 1, pp. 19–27, Jan. 2011.

[30] A. Darwish, "Bio-inspired computing: Algorithms review, deep analysis, and the scope of applications," *Future Comput. Informat. J.*, vol. 3, no. 2, pp. 231–246, Dec. 2018.

[31] Q. Bai, "Analysis of particle swarm optimization algorithm," *Comput. Inf. Sci.*, vol. 3, no. 1, p. 180, Jan. 2010.

[32] A. A. A. Esmin, G. Lambert-Torres, and G. B. Alvarenga, "Hybrid evolutionary algorithm based on PSO and GA mutation," in *Proc. 6th Int. Conf. Hybrid Intell. Syst. (HIS)*, Dec. 2006, p. 57.

[33] Z. Zheng, S. Dai, and X. Xie, "Research on fault detection for ZPW-2000A jointless track circuit based on deep belief network optimized by improved particle swarm optimization algorithm," *IEEE Access*, vol. 8, pp. 175981–175997, 2020.

[34] P. Zhi, Y. Li, B. Chen, X. Bai, and Z. Sheng, "Fuzzy design optimization-based fatigue reliability analysis of welding robots," *IEEE Access*, vol. 8, pp. 64906–64917, 2020.

[35] M. G. Sim oes and F. A. Farret, *Modeling Power Electronics and Interfacing Energy Conversion Systems*. Hoboken, NJ, USA: Wiley, 2017. [Online]. Available: http://cds.cern.ch/record/2230202

[36] J. P. Mo, S. C. Cheung, and R. Das, "Basic numerical techniques," in *Demystifying Numerical Models*, J. P. Mo, S. C. Cheung, and R. Das, Eds. Oxford, U.K.: Butterworth-Heinemann, 2019, pp. 5–31.

HESAM MAZAHERI (Graduate Student Member, IEEE) was born in Qazvin, Iran, in 1988. He received the B.Sc. degree in electrical engineering and the M.Sc. degree in mechatronic engineering from Qazvin Islamic Azad University, Qazvin, in 2011 and 2014, respectively. He is currently pursuing the Ph.D. degree with the Universidad Politécnica de Madrid (UPM).

His interests include microgrids and stability assessment of electronic power distribution systems.

AIRÁN FRANCÉS (Member, IEEE) received the M.Sc. and Ph.D. degrees in electrical engineering from the Universidad Politécnica de Madrid (UPM), Spain, in 2012 and 2018, respectively.

He is currently an Assistant Professor with the Department of Electrical Engineering, UPM. He has participated in the European Project XFEL for two years, where he collaborated in the design and development of dc–dc power supplies for superconducting magnets. His current research interests include modeling, control, and stability assessment of electronic power distribution systems, and smart grids.

RAFAEL ASENSI was born in Madrid, Spain, in 1966. He received the M.Sc. and Ph.D. degrees in electrical engineering from the Universidad Politécnica de Madrid (UPM), Madrid, in 1991 and 1998, respectively.

In 1994, he joined the Department of Electrical Engineering, where he is currently an Associate Professor. His research interests include high-frequency modeling of magnetic components and non-linear load modeling and simulation.

JAVIER UCEDA (Life Fellow, IEEE) received the M.Sc. and Ph.D. degrees in electrical engineering from the Universidad Politécnica de Madrid (UPM), Spain, in 1976 and 1979, respectively.

He is currently a Full Professor in electronics with the Electrical and Electronic Engineering Department, UPM. His research activity has been developed in the field of power electronics, where he has participated in numerous national and international research projects. As a result of this activity, he has published more than 300 articles in international journals and conferences. He holds several national and international patents. His research interests include switched-mode power supplies and dc–dc power converters for telecom and aerospace applications.

Prof. Uceda received several individual and collective awards, such as the IEEE Third Millennium Medal and the Puig Adam Medal. He was awarded an Honorary Doctorate by the Universidad Ricardo Palma, Peru, and the Colegio de Postgraduados, Mexico.