Assessment of Parameter Identification Methods for Digital Twins of Two-Level Bidirectional Converters

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***Abstract*—Monitoring and maintaining the health and performance of power electronic converters is of paramount importance in many applications. The use of digital twins for this purpose has received significant attention over the last few years. System parameter identification will be critical for the development of accurate and reliable digital twins. In this paper, the application of digital twin technology for monitoring a two-level bidirectional converter is explored, with a special focus on the selection of algorithms for parameter identification, and their implementation. While Particle Swarm Optimization (PSO) has gained increased attention in power converter applications recently, it does not necessarily produce the best results. Both simulation and experimental verification will be used to validate the findings. The final use of the proposed methods is onboard energy storage integration for railways. However, the conclusions reached in this paper can be extended to other applications as well as power converter topologies.**

***Index Terms*—Digital twin, Interior point method, PSO, Two-level DC/DC bidirectional converter**

I. Introduction

Power converters are sensitive to failure owing to the degradation of components, either due to normal aging, manufacturing imperfections, or stressing modes of operation [1]. Enhancing the reliability of power converters is a challenging task for practically all applications [2]. Monitoring these systems offers several benefits. It allows early identification of critical situations to prevent total or partial functional loss [3]. Also, it enables the monitoring of both passive and active components, ensuring the overall health and performance of the converter [4, 5]. Additionally, monitoring techniques can be easily applied to different converter topologies while maintaining the same theoretical basis [6].

In recent years, researchers have led the way in developing innovative methodologies for estimating the health indicators of DC-DC converters, as highlighted by [7]. Interest in monitoring the condition of power electronics converters has grown significantly, particularly with the introduction of digital twin technology. A digital twin functions as a virtual duplicate of the physical converter, working alongside its physical counterpart. By continuously receiving data from sensors embedded in the physical system, the digital twin accurately mirrors real-world behavior, ensuring precise representation and dynamic adaptation to changes in the converter's operational environment[8]. The integration of digital twin technology into power systems has experienced extensive exploration. In [9], the applications of IoT and digital twin for condition monitoring and diagnosis were explored within electrical power systems. In [10], there has been notable progress in developing controller-embeddable probabilistic real-time digital twins customized for power electronic converter diagnostics. These advancements leverage digital twin concepts to enable more accurate condition monitoring, empowering proactive maintenance strategies and boosting system reliability. Moreover, these digital twins offer dynamic real-time monitoring capabilities, enabling the integration of probabilistic logic for diagnostic purposes.

Ensuring alignment between the parameters of a digital twin and its physical counterpart is essential. Several algorithms have been proposed to identify relevant system parameters in real time. In [7, 11–14], Particle Swarm Optimization (PSO) is employed for parameter identification purposes in power converters. In [15], Bayesian methods are employed for identification purposes, while [16] utilizes Polynomial Chaos Expansion (PCE) for similar objectives. The performance of each method can depend on multiple aspects, including the dynamic properties of the parameter being identified, sampling rates and, errors in the measurement/estimation of inputs and outputs.

This paper is aimed to provide a comprehensive analysis of parameter identification methods in power converter applications. Although the paper focuses on a particular case of a two-

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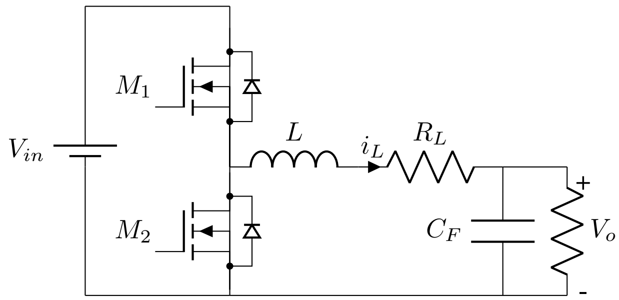

Fig. 1. Two-level bidirectional DC-DC converter

level bidirectional DC/DC converter, the proposed approach is extendable to any power converter topology. Special focus is given to Interior Point Method (IPM) and PSO, as they were found to provide the best results.

The paper is organized as follows: In Section II a mathematical model for a two-level DC-DC bidirectional converter is derived. In Section III, the cost function is introduced, and the IPM is compared to PSO and presented as a preference for parameter identification. Using these steps, a real-time digital twin is designed. In Section IV the digital twin is validated through simulation, and experimentally later, in Section V a down-scaled prototype of the two-level DC-DC bidirectional converter is used for validation. Finally, conclusions are presented in Section VI.

II. Mathematical Model of the Two-level Bidirectional Converter

In this section, the development of a mathematical model of the two-level bidirectional power converter is addressed. Fig.1 shows the power converter being considered for the analysis. It comprises two MOSFETs, an inductor with a series parasitic resistance, and an output capacitor. A resistive load is considered. The circuit equations can be seen in (1)-(2), where $D(t)$ and $D'(t)$ represent the pulse-width modulation (PWM) signals for the upper and lower MOSFETs respectively; V_{in} indicates the input voltage; V_c represents the voltage across the output capacitor, I_L denotes the inductor current, V_f represents the forward voltage of the MOSFET's body diode; L_f and R_f indicate the inductance and resistance of the inductor respectively; R_d signifies the body diode's conductance resistance; $R_{ds(on)}$ represents the MOSFET's conductance resistance.

$$C\frac{dV_c}{dt} = I_L - \frac{V_c}{R_{load}} \tag{1}$$

$$L\frac{dI_L}{dt} = D(V_{in} - R_{ds(on)}I_L) - D'(V_f + R_dI_L) - R_fI_L - V_c \tag{2}$$

Fig.2 drafts the concept of the digital twin utilized in this paper. Two Sample and Hold (S&H) blocks are utilized: one operates at the control sampling frequency for control purposes, while the other functions at a much higher frequency dedicated to the digital twin. The outputs of the converter and digital twin are compared using a cost function, allowing for parameter updates through a parameter identification algorithm. Additionally, the results are sent to a processing block for parameter monitoring or fault detection.

As already mentioned, the digital twin generates outputs that are compared with those of the physical system in each digital twin time step. To accomplish this, discretization of the equations of the converter is required. Backward Euler method was employed with a sampling time of T_s. The outcomes of this discretization are displayed in (3) and (4). k represents the current sample, and the next sample is denoted as $k+1$.

$$\begin{aligned} I_L[k+1] = I_L[k] + \frac{T_s}{L}(D[k](V_{in} - R_{ds(on)}I_L[k]) \\ - D'[k](V_f + R_dI_L[k]) - R_fI_L[k] - V_c[k]) \end{aligned} \tag{3}$$

$$V_c[k+1] = \frac{V_c[k] + T_sI_L[k+1]/C}{1 + \frac{T_s}{CR_{load}}} \tag{4}$$

In the discretization procedure, it is essential to employ a sufficiently high sampling frequencies. Otherwise aliasing will occur, making system parameters identification unfeasible.

III. Parameter Identification

Parameter identification refers to the process of determining the values of unknown parameters in a mathematical model or system based on observed data or experimental measurements[17]. Accurate parameter identification is essential for properly characterizing the behavior and performance of the system.

A. Cost Function

The cost function, or objective function, is crucial in parameter identification. It measures the difference between observed data and model predictions using current parameter values. The main goal of parameter identification is to minimize this cost function, ensuring the best possible match between the model and the behavior of the real-world system. During the iterative process across multiple time steps, the cost function is computed at each step. The cost function is of the form shown in 5 and evaluates at every time step the variance between the system outputs, I_{Lm} and V_{om}, and the corresponding values, I_{Ld} and V_{od}, provided by the digital twin. Coefficients a_1 and a_2 are the weighting factors that determine the influence of each term of the cost function.

$$f_{ob} = \frac{1}{N}\sum_{k=1}^{N}\Big(a_1\left(I_{Ld}[k] - I_{Lm}[k]\right)^2 + a_2\left(V_{od}[k] - V_{om}[k]\right)^2\Big) \tag{5}$$

B. Optimization Techniques for Parameter Identification

In this section, two optimization methodologies for parameter identification are explored: IPM and PSO. While PSO has seen broad utilization in power converter applications, IPM is proposed as an alternative approach. The aim is to develop a

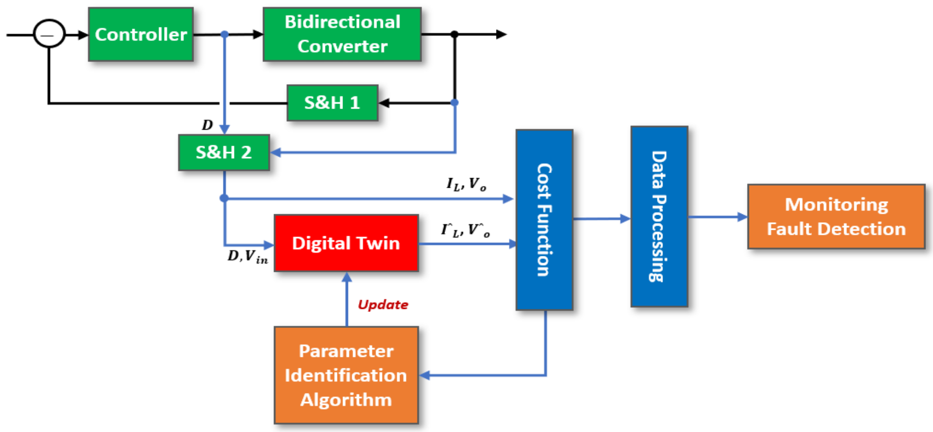

Fig. 2. Digital twin concept for DC/DC converters

methodology for the effective selection and utilization of these techniques.

1) Interior Point Method : IPM is a deterministic optimization algorithm widely utilized for solving large-scale nonlinear programming problems. It operates by iteratively refining the solution to approach the optimal point within a feasible region while satisfying constraints. One advantage of IPM is its efficiency in handling complex optimization tasks. However, challenges may be encountered with multimodal functions and local minima [18, 19]. The update equations of IPM are as follows:

- Primal Update:

$$x^{k+1} = x^k + \alpha^k \Delta x^k \tag{6}$$

- Dual Update:

$$y^{k+1} = y^k + \beta^k \Delta y^k \tag{7}$$

- Complementarity Gap Update:

$$\mu^{k+1} = \mu^k + \gamma^k \Delta \mu^k \tag{8}$$

where, x^k and y^k represent the primal and dual variables respectively at iteration k. Δx^k and Δy^k are the primal and dual updates computed at each iteration; α^k, β^k, and γ^k are step sizes chosen to ensure convergence; μ^k is the complementarity gap, and $\Delta\mu^k$ is the update to the complementarity gap for iteration k [20].

2) Particle Swarm Optimization: PSO is a stochastic optimization algorithm inspired by the social behavior of organisms such as bird flocking or fish schooling. In PSO, a swarm of particles explores the search space to find the optimal solution by adjusting their positions based on the best solutions found by themselves and their neighbors [21, 22]. PSO is known for its simplicity, ease of implementation, and robustness against local optimums. However, more iterations may be required to converge compared to IPM. The update equations of PSO are as follows:

- Velocity Update:

$$v_i^{t+1} = \omega \cdot v_i^t + c_1 \cdot r_1 \cdot (pbest_i^t - x_i^t) + c_2 \cdot r_2 \cdot (gbest^t - x_i^t) \tag{9}$$

- Position Update:

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{10}$$

where, v_i^t and x_i^t represent the velocity and position of particle i at iteration t respectively. $pbest_i^t$ denotes the best position found by particle (personal best) i so far, and $gbest^t$ is the best position found by any particle (global best) in the swarm at iteration t; constants ω, c_1, and c_2 are the inertia, cognitive, and social parameters respectively; r_1 and r_2 are random numbers uniformly distributed in the range [0, 1] [23].

Table I offers a comparative analysis between the IPM and PSO across several criteria. In terms of speed, precision, convergence, robustness, and scalability, IPM generally beats PSO, as indicated by the upward arrows (↑) denoting superiority in these aspects. IPM demonstrates faster convergence, higher precision, and greater robustness compared to PSO. However, PSO holds an advantage in terms of diversity, providing higher diversity compared to IPM. Both IPM and PSO offer global optimization, with IPM featuring multi-start capabilities, denoted by (*). Furthermore, PSO is relatively easy to implement. The choice between IPM and PSO ultimately depends on the specific requirements and constraints of the optimization problem at hand.

IV. Simulation Results

In this section, simulations are conducted using Simulink MATLAB to assess the performance of IPM and PSO. The process of convergence of PSO with the number of iterations is shown in Fig.3. A similar analysis was performed for IPM, as shown in Fig.4. Table II presents the iterative process of IPM implemented in MATLAB, displaying the values of the cost function and tolerance at each iteration. Following the identification of parameters, a comparison between the digital twin model and the physical converter is undertaken, utilizing the identified parameters and mathematical model explained

TABLE I
COMPARISON OF IPM AND PSO

Criteria	IPM	PSO
Speed	⇑	⇓
Precision	⇑	⇓
Convergence	⇑	⇓
Robustness	⇑	⇓
Scalability	⇑	⇓
Global Optimization	*	⇑
Ease of Implementation	⇑	⇑
Diversity	⇓	⇑

** with multi-start*

⇑ and ⇓ stand for advantageous and disadvantageous respectively

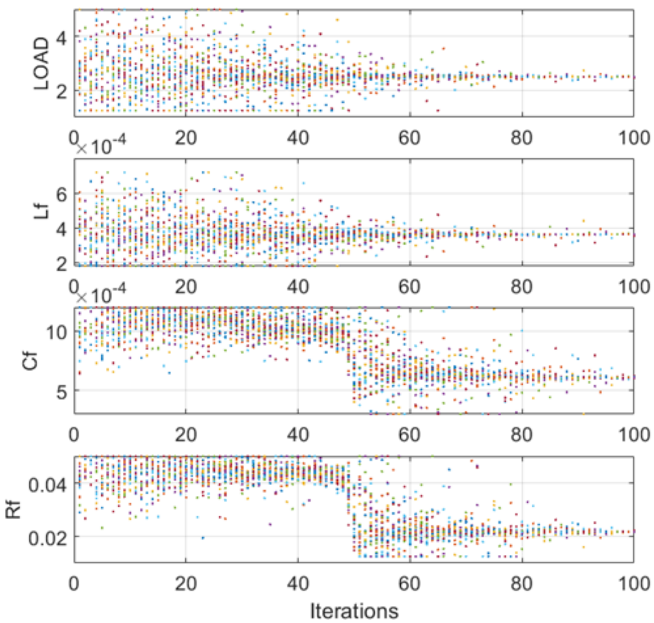

Fig. 3. PSO convergence vs. number of iterations

in the preceding sections.Fig.5 illustrates the accuracy of the model in replicating the behavior of the converter, particularly in response to a step change in duty cycle value.

V. EXPERIMENTAL RESULTS

To validate the digital twin model and assess the performance of various algorithms for parameter identification, a down-scaled two-level bidirectional converter was implemented. The converter operates at a switching frequency of 20 kHz and a sampling frequency. The control sampling frequency is also 20 kHz, and signals are sampled at 625 MHz using the Yokogawa DLM2024 oscilloscope with Yokogawa current probe 700937. It can also be sampled with lower frequencies, such as 1 MHz. The output voltage is set to 300 V. Further details can be found in Table IV. Fig.6 displays a visual representation of the implemented converter. The experimental setup involved operating the converter in parallel with its corresponding digital twin model while continuously updating the parameters. Throughout the experimentation pro-

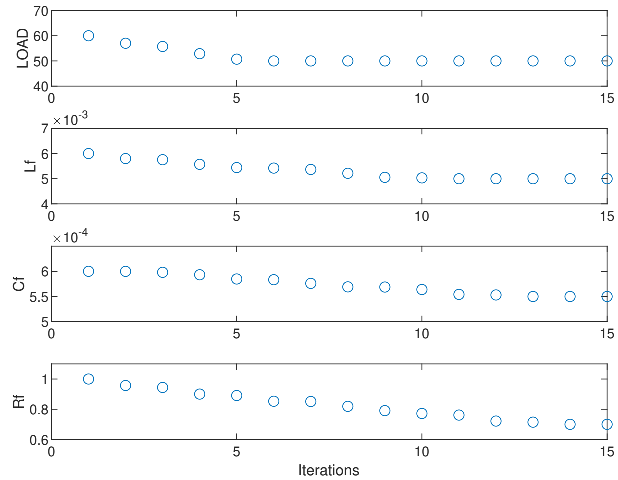

Fig. 4. IPM convergence vs. number of iterations

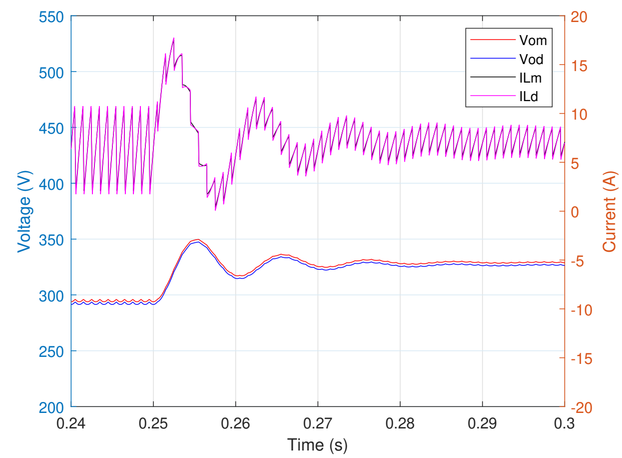

Fig. 5. Simulation results: physical system vs. digital twin inductor current and capacitor voltage after a step in duty cycle

TABLE II
INTERIOR POINT ITERATIONS TO FIND OPTIMAL RESULTS

Iter	F-count	$f(x)$	Optimality	Norm of step
0	5	7.844789e-02	1.834e+02	
1	19	6.810543e-02	2.271e-01	1.192e-02
2	25	5.048364e-02	1.569e+02	4.419e-01
3	32	3.509114e-02	1.266e+02	1.034e-02
4	38	3.230926e-02	3.336e+02	2.450e-01
5	46	1.748181e-02	1.202e+02	6.960e-02
6	53	7.820915e-03	1.522e+01	1.867e-01
7	58	2.110241e-03	2.814e+00	5.500e-02
8	63	2.077175e-03	1.488e+00	5.346e-03
9	68	2.073470e-03	1.458e+00	4.305e-04
10	73	2.074238e-03	3.265e-02	1.679e-04
11	78	2.074206e-03	4.337e-02	3.192e-04
12	83	2.073536e-03	1.225e-01	1.845e-03
13	88	2.070151e-03	1.703e-01	8.990e-03
14	93	2.061799e-03	4.989e-02	3.304e-02
15	98	2.061813e-03	9.641e-03	4.878e-04

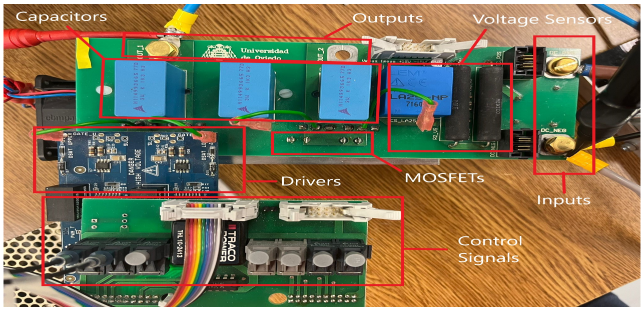

Fig. 6. Two-level bidirectional converter prototype

TABLE III
CONFIGURATION USED FOR IPM AND PSO

PSO		IPM	
Type	Global	Type	Nonlinear Constrained
Max Iter	100	Max Iter	100
Pop	50	Max Func Eval	1000
TolFun	2×10^{-6}	ConsTol	3×10^{-6}
ω	1	Step Size Tol	1×10^{-5}
δ	0.99	Opt Tol	1×10^{-6}
Soc Acc	2		
Per Acc	2		

cess, the accuracy of the digital twin's output was assessed and analyzed.

Table IV presents the outcomes obtained from both the IPM and PSO with configuration mentioned in Table III in comparison with the measured data of critical parameters. The analysis demonstrates that, in experimental conditions, the interior point method exhibits superior accuracy and fewer faults compared to PSO, particularly when there are noises present during the sensing of values.

Fig.7 provides a visual representation of the alignment between the output of the digital twin and the actual behavior exhibited by the converter.

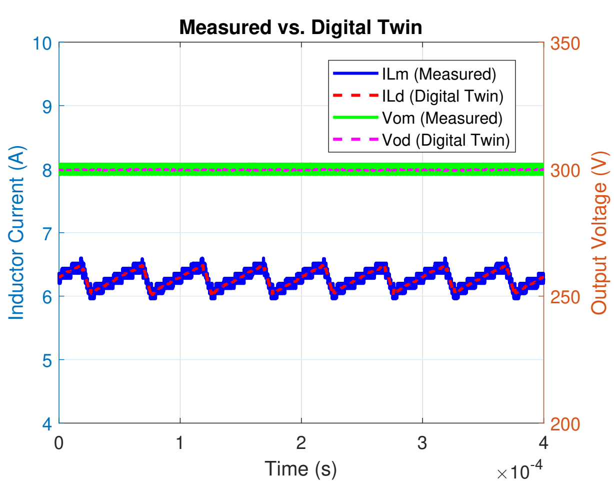

Fig. 7. Comparison between voltages and currents in physical converter and digital twin model

TABLE IV
IDENTIFICATION RESULTS WITH MEASUREMENTS

Symbol	Measurements	IPM	PSO
L_f	5 mH	4.99 mH	4.26 mH
R_f	700 mΩ	698 mΩ	623 mΩ
C_f	550 μ F	550 μ F	503 μ F
$R_{ds(on)}$	125m Ω	126 mΩ	147 mΩ

VI. CONCLUSIONS

In this paper, PSO and IPM have been evaluated for parameter identification for the digital twin of a two-level DC/DC power converter. The benefits of IPM including speed of convergence, precision, and consistency in producing reproducible results with the same input, are highlighted. A digital twin model is developed to replicate the behavior of a two-level bidirectional converter using the parameters that were found by the identification algorithm. Validation of the model was carried out using a down-scaled prototype. Simulation and experimental results have been provided to support the proposed method. Although the paper focuses on a two-level DC/DC converter, the proposed methodology can be applied to any power converter topology.

REFERENCES

[1] M. Sujatha and A. K. Parvathy. "Investigation of Reliability of DC–DC Converters Using Reliability Block Diagram and Markov Chain Analysis". In: (2020). Ed. by P. V. Varde, R. V. Prakash, and G. Vinod, pp. 851–863.

[2] E. Rachev and V. Petrov. "DC link capacitor selection for DC-DC converters". In: (2020), pp. 1–5. DOI: 10.1109/BulEF51036.2020.9326085.

[3] M. Bindi, G. Talluri, G. M. Lozito, A. Luchetta, M. C. Piccirilli, and F. Grasso. "Smart monitoring of DC-DC converters". In: *2022 IEEE International Conference on Environment and Electrical Engineering and 2022 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe)*. 2022, pp. 1–6. DOI: 10.1109/EEEIC/I&CPSEurope54979.2022.9854667.

[4] J. Chen, M.-K. Nguyen, Z. Yao, C. Wang, L. Gao, and G. Hu. "DC-DC Converters for Transportation Electrification: Topologies, Control, and Future Challenges". In: *IEEE Electrification Magazine* 9.2 (2021), pp. 10–22. DOI: 10.1109/MELE.2021.3070934.

[5] K. Kahen. "Hybrid power source with a high voltage capacitor and methods of manufacturing the same". May 2011. URL: https://patents.google.com/patent/WO2011010141A3.

[6] M. K. Kazimierczuk. "Method and system for DC to DC power conversion". Aug. 2013. URL: https://patents.google.com/patent/US8519691.

[7] Y. Peng, S. Zhao, and H. Wang. "A digital twin based estimation method for health indicators of dc–dc converters". In: *IEEE Transactions on Power Electronics* 36 (2 2021), pp. 2105–2118. DOI: 10.1109/tpel.2020.3009600.

[8] A. Rasheed, O. San, and T. Kvamsdal. "Digital Twin: Values, Challenges and Enablers From a Modeling Perspective". In: *IEEE Access* 8 (2020), pp. 21980–22012. DOI: 10.1109/ACCESS.2020.2970143.

[9] D. A. Mansour, M. Numair, A. S. Zalhaf, R. Ramadan, M. M. F. Darwish, Q. Huang, M. G. Hussien, and O. Abdel-Rahim. "Applications of iot and digital twin in electrical power systems: a comprehensive survey". In: *IET Generation, Transmission Amp; Distribution* 17 (20 2023), pp. 4457–4479. DOI: 10.1049/gtd2.12940.

[10] M. Milton, C. D. L. O, H. L. Ginn, and A. Benigni. "Controller-embeddable probabilistic real-time digital twins for power electronic converter diagnostics". In: *IEEE Transactions on Power Electronics* 35 (9 2020), pp. 9850–9864. DOI: 10.1109/tpel.2020.2971775.

[11] Y. Liu, G. Chen, Y. Liu, L. Mo, and X. Qing. "Condition Monitoring of Power Electronics Converters Based on Digital Twin". In: (2021), pp. 190–195. DOI: 10.1109/ICCS52645.2021.9697303.

[12] M. T. Fard and J. He. "Digital Twin Health Monitoring of Five-Level ANPC Power Converter based on Estimation of Semiconductor On-State Resistance". In: (2023), pp. 1–7. DOI: 10.1109/IAS54024.2023.10406700.

[13] G. Di Nezio, M. Di Benedetto, A. Lidozzi, and L. Solero. "Digital Twin based Real-Time Analysis of DC-DC Boost Converters". In: (2022), pp. 1–7. DOI: 10.1109/ECCE50734.2022.9947394.

[14] G. Di Nezio, S. Diz, M. Benedetto, A. Lidozzi, E. Peña, and L. Solero. "Parameters Estimation of a 3-Phase AC-DC Converter based on the Digital Twin Method". In: (Oct. 2023), pp. 2937–2944. DOI: 10.1109/ECCE53617.2023.10362069.

[15] S. Chen, S. Wang, P. Wen, and S. Zhao. "Digital Twin for Degradation Parameters Identification of DC-DC Converters Based on Bayesian Optimization". In: (2021), pp. 1–9. DOI: 10.1109/ICPHM51084.2021.9486446.

[16] M. Milton, C. D. L. O, H. L. Ginn, and A. Benigni. "Controller-Embeddable Probabilistic Real-Time Digital Twins for Power Electronic Converter Diagnostics". In: *IEEE Transactions on Power Electronics* 35.9 (2020), pp. 9850–9864. DOI: 10.1109/TPEL.2020.2971775.

[17] S. Padhee, U. C. Pati, and K. Mahapatra. "Modelling switched mode DC-DC converter using system identification techniques: A review". In: *2016 IEEE Students' Conference on Electrical, Electronics and Computer Science (SCEECS)*. 2016, pp. 1–6. DOI: 10.1109/SCEECS.2016.7509303.

[18] I. Pólik and T. Terlaky. "Interior Point Methods for Nonlinear Optimization". In: *Nonlinear Optimization: Lectures given at the C.I.M.E. Summer School held in Cetraro, Italy, July 1-7, 2007*. Ed. by G. Di Pillo and F. Schoen. Berlin, Heidelberg: Springer Berlin Heidelberg, 2010, pp. 215–276. ISBN: 978-3-642-11339-0. DOI: 10.1007/978-3-642-11339-0_4. URL: https://doi.org/10.1007/978-3-642-11339-0_4.

[19] C. M. Ladislav Lukšan and J. Vlček. "Interior point methods for large-scale nonlinear programming". In: *Optimization Methods and Software* 20.4-5 (2005), pp. 569–582. DOI: 10.1080/10556780500140508. eprint: https://doi.org/10.1080/10556780500140508. URL: https://doi.org/10.1080/10556780500140508.

[20] F. A. Potra and S. J. Wright. "Interior-point methods". In: *Journal of Computational and Applied Mathematics* 124.1 (2000). Numerical Analysis 2000. Vol. IV: Optimization and Nonlinear Equations, pp. 281–302. ISSN: 0377-0427. DOI: https://doi.org/10.1016/S0377-0427(00)00433-7. URL: https://www.sciencedirect.com/science/article/pii/S0377042700004337.

[21] J. H. Lee, J.-W. Kim, J.-Y. Song, Y.-J. Kim, and S.-Y. Jung. "A Novel Memetic Algorithm Using Modified Particle Swarm Optimization and Mesh Adaptive Direct Search for PMSM Design". In: *IEEE Transactions on Magnetics* 52.3 (2016), pp. 1–4. DOI: 10.1109/TMAG.2015.2482975.

[22] A. E. Olsson. "Particle Swarm Optimization: Theory, Techniques and Applications". In: 2010. URL: https://api.semanticscholar.org/CorpusID:106654712.

[23] D. Wang, D. Tan, and L. Liu. "Particle swarm optimization algorithm: an overview". In: *Soft Computing* 22.2 (2018), pp. 387–408. ISSN: 1433-7479. DOI: 10.1007/s00500-016-2474-6. URL: https://doi.org/10.1007/s00500-016-2474-6.