Digital Twin Based Identification of Passive Parameters of Three-phase Boost Rectifier using a GRU Neural Network

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***Abstract*—Condition and health monitoring in power electronics are becoming more and more important and are increasingly discussed in articles in the literature. To timely intervene in fault detection or remaining useful life (RUL) estimation for predictive maintenance operations, artificial intelligence (AI) and neural networks (NNs) can be useful also to estimate the health status of the components. In this paper a digital twin-based parameters identification method of an AC-DC converter is proposed using the Gated Recurrent Unit (GRU) NN. The dataset has been created without the need of any additional hardware, using only the sensors already present in the power conversion system to perform the control action. The training of the GRU NN has been performed in Matlab environment and the obtained results of the predicted parameters are presented to validate the proposed monitoring method. Furthermore, the closed form of the GRU NN has been implemented in the microprocessor present on the control board PED-Board through LabVIEW Real-Time graphical programming code. Finally, the experimental results of the parameters identification in real-time are presented.**

Keywords—Parameters Identification, AC-DC Converter, Neural Networks, Machine Learning, Gated Recurrent Unit (GRU)

I. INTRODUCTION

Nowadays we often discuss about artificial intelligence (AI) from an ethical point of view, but above all from an innovative scientific point of view. Thanks to AI and machine learning (ML), today technology is able to achieve goals that were unimaginable just a few years ago. This topic has also become widespread in the power electronics sector [1]. AI has so far been applied to power electronics to realize advanced control algorithms, such as maximum power point tracking (MPPT) for wind energy conversion systems [2]. Moreover, applications concerning the maintenance and the design of power electronic converters (PECs) have also been developed recently. As an example, in [3] a reinforcement-learning-based framework that generates power converter topology candidates based on user specifications is proposed. Thanks to AI, the optimization of many important attributes, such as power efficiency, layout size, cost, heat dissemination has been reached. In predictive maintenance for PECs there are several applications for the AI too: the most studied are anomaly detection and RUL estimation. In [4] the Gaussian process regression (GPR) method is applied to learn the normal behaviour of DC-DC converters with unknown circuit structures and the genetic algorithm (GA) is applied for evaluating maximum and minimum statistical values for anomaly detection. A linear regression method for anomaly detection in photovoltaic inverters is proposed in [5]. Regarding estimating RUL, artificial NNs (ANNs) are starting to gain traction over the methods with analytical prediction models. Indeed, in [6] a comparative study between the analytical model prediction of an insulated gate bipolar transistor (IGBT) and the number of cycles to failure of the same power semiconductor device evaluated by the ANN has been carried out, confirming that the latter are able to find complex correlations between inputs and output that could be difficult for conventional analytical models.

This paper delves into the identification of passive parameters of a PEC. Accurately identifying these parameters is crucial as it lays the foundation for advanced diagnostic processes, such as the anomaly detection and the RUL estimation, thereby facilitating predictive maintenance and enhancing the overall lifecycle management of power electronic systems. There are several strategies for identifying parameters, even if in PECs it is challenging due to higher and higher switching frequencies, several disturbing elements and small variations of parameters over time [7]. Furthermore, in order not to introduce additional disturbances and not increase the complexity of the system, monitoring methods without additional hardware are used. One way is to recreate the model under examination through physics-based methods. In [8] the PEC magnetic components and their position on the circuit board are modelled numerically using finite element analysis (FEA) in order to evaluate the electromagnetic interference. A physic based Simscape model of a SiC MOSFET has been realized in [9] to extrapolate the currents and voltages of interest for estimating the health status. Another non-invasive monitoring strategy is to use the optimization algorithms to identify the parameters health status over time. In particular, recently, this technique has been fused to the physics based one, generating the digital twin (DT) monitoring method. In [10] the DT of a DC-DC boost converter has been implemented, realizing the real-time digital model based on the state space equations representation and using as optimization algorithm the particle swarm optimization (PSO). The same methodology has been applied in [11] to identify the passive parameters of an AC-DC converter. However, the PSO is an iterative optimization algorithm, which takes time to estimate the parameters and, by increasing the number of unknown parameters, it becomes more and more inaccurate. For this reason, AI is emerging in the parameters' estimation in PECs scenario. The DT of a DC-DC buck converter has been implanted in [12] using the Nonlinear AutoRegressive eXogenous (NARX) recurrent neural network (RNN). In [13] the capacitance estimation of a DC-link capacitor in a back-to-back converter has been reached through an ANN architecture using as input only the RMS value of the input current and the voltage ripple of the DC-link voltage. The identification of all the parameters of a buck converter has been achieved in [14], in which time and frequency domain features have been extracted by the current and voltage signals to train a back propagation (BP) NN. Despite good results are shown in [14], only using simulation data is not convincing to validate a NN based method. The experimental validation regarding the identification of the on-state resistance of a MOSFET and the output capacitor's capacitance and its series resistance in a DC-DC buck converter has been provided in [15]. In particular, the proposed ANN method consists of two networks, ANN1 used to identify the on-state resistance of the MOSFET and ANN2 to estimate the capacitance and the capacitor series resistance for reducing the estimation error of the parameters. In [16] a monitoring method for the deterioration parameters of a DC-DC boost converter has been realized through the use of a NN and the comparison with a PSO health monitoring technique is carried out, demonstrating the improvement of the relative error in the parameters' estimation. In [17] the Physics-Informed Neural Networks (PINNs) has been reached to estimate the degradation parameters of a buck converter deriving the physical formula of the DC-DC converter through the state-space average method and adding them to the deep learning model of long-short term memory (LSTM) NN. In [18] a PINN has been proposed to predict both the waveforms of the current and voltage of a DC-DC buck converter and its deterioration parameters. In this paper the parameters identification of a three-phase AC-DC converter has been carried out through a gated recurrent unit (GRU) NN. In particular, the three-phase inductance of the AC-DC boost rectifier and the capacitance value of the DC-link capacitor are identified. The architecture of the network and why to use a GRU instead of the more famous LSTM NN are discussed in detail. The paper is organized as follows: in Section II the dataset selection and creation are discussed, and the methodology is illustrated; in Section III the advantages and disadvantages of the GRU are compared to others NNs and the final NN is presented; experimental results in Typhoon HIL and LabVIEW environment are shown in Section IV; finally, conclusions are discussed in Section V.

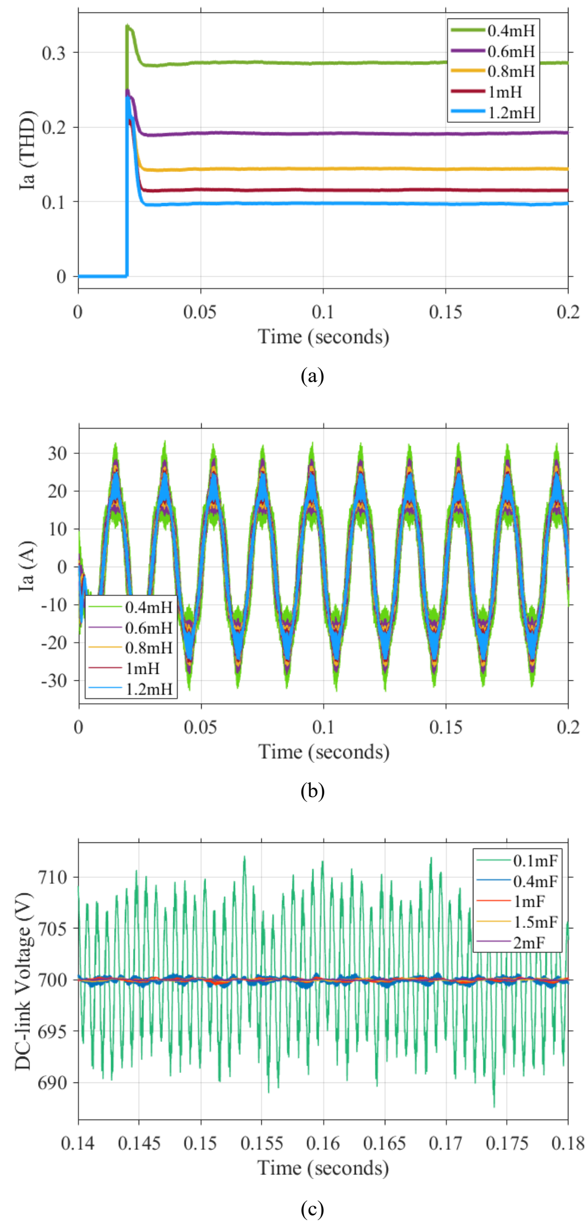


Fig. 1. Selected waveforms for the NN dataset: (a) THD of the phase current for different inductance values; (b) the phase current waveform for different inductance values; (c) the DC-link voltage ripple for different capacitance values.

II. DATASET CREATION

Since in an AC-DC converter there are generally voltage sensors on the DC-link and current sensors on the three phase currents for the control action, the dataset has been created starting from these signals, with the aim of not inserting additional hardware. The objective of the study carried out is to find the signals more sensitive to the variation of the parameters of interest. In particular, the total harmonic distortion (THD) of the phase currents has been selected because of the strong dependance on the three phase inductances L_a, L_b, and L_c, as shown in Fig. 1a. Moreover, the phase currents too have been considered in the dataset formulation, represented in Fig. 1b. Regarding the capacitance C, the signal dependent on its value is the DC-link voltage, as shown in Fig. 1c. Because of this, the definitive dataset is composed by 7 signals: the THD of the three phase currents, the three phase currents waveforms, and the DC-link voltage waveform. The dataset has been carried out by means of the Typhoon Hardware-In-the-Loop (HIL) 606, shown in Fig. 2. First a random target of 10000x4 values has been realized by randomly varying the inductances between 400µH and 1.2mH and the capacitance between 0.1mF and 2mF. Then, thanks to Typhoon HIL *Variable Passive Components* library, the randomly chosen parameters are set to perform the data mining. Each signal has been sampled at a sampling frequency of 100kHz considering two fundamental periods, where the fundamental frequency has been set equal to 50 Hz. The characteristics of the final dataset have been reported in Table I.

TABLE I. DATASET DEFINITION

Samples Dimension	***Dataset Dimension***	***Train Percentage***	***Validation Percentage***	***Test Percentage***
7x4000	10000x1	80%	10%	10%

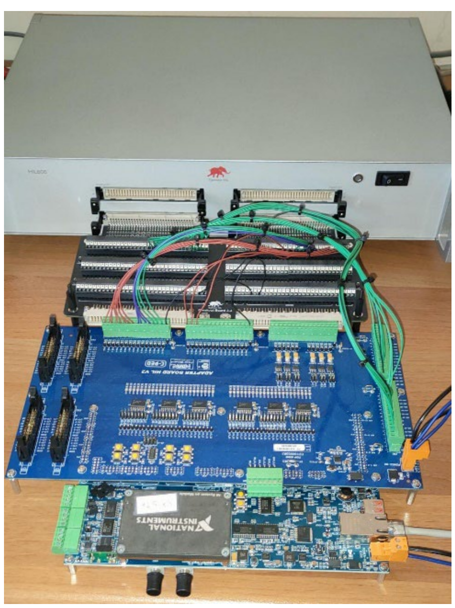


Fig. 2. Typhoon HIL 606 setup.

III. GATED RECURRENT UNIT (GRU) NEURAL NETWORK

The NN selected in this work is the GRU. GRU NN is a type of recurrent neural network (RNN) that has gained popularity due to its simpler architecture: it is a cyclic network that uses the

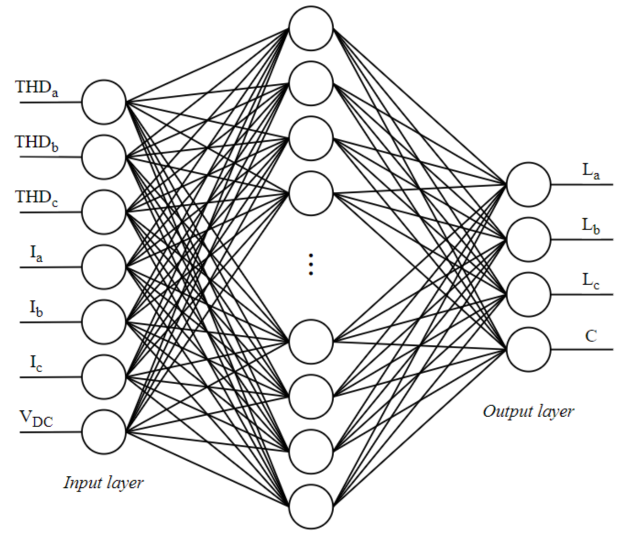


Fig. 3. NN architecture.

output values of a certain level as input for the next level, thus creating feedback and a correlation between past and future values [19]. Therefore, it has the added feature of being able to learn the input series and store them in memory, thanks to gates that control the passage of information, retaining important information over long sequences and discarding irrelevant data. In this way, GRUs, like LSTMs, are designed to handle the vanishing gradient problem that plagues traditional RNNs. Moreover, GRUs have a simpler structure than LSTMs, with fewer parameters to train, which can result in faster training times and reduced computational costs. However, GRUs lack an explicit output gate, which is present in LSTMs and can be beneficial for certain tasks where controlling the output flow is crucial. In this application an RNN was necessary because of the sequence to one regression, however controlling the output flow is not a key factor. For this reason, a GRU NN architecture has been selected for this work. The final architecture of the NN used in this paper, illustrated in Fig. 3, consists in a single hidden layer composed by 64 neurons. The training has been done in the Matlab-Simulink environment and the training options are reported in Table II.

TABLE II. TRAINING OPTIONS OF THE NEURAL NETWORK

Training Options	
Hyperparameter	***Value***
Hidden Layer	1
Hidden Units	64
Optimizer	*adam*
Learning Rate	0.005 (*constant*)
Max Epochs	250
Minibatch Size	64

A. GRU Closed Form Representation

Even if the training of the network has been performed offline using the Matlab Deep Learning Toolbox, for the experimental validation the NN has to be moved to LabVIEW environment in order to run on the selected control board. However, Matlab permits to save the trained network in a no suitable form for the LabVIEW Real-Time environment. That's why the closed form representation of the GRU NN has been derived [19], where the closed form stands for the equation describing the network. At first the input is normalized using the *zscore* Matlab normalization function. Then, the GRU hidden layer is realized. In particular, the GRU NN is composed by: a reset gate r_t which determines how much of the previous hidden state h_{t-1} to forget; an update gate z_t that decides how much of the new candidate activation $\tilde{h}_t$ will be used to update the hidden state h_t; the candidate activation $\tilde{h}_t$ representing the potential new hidden state, incorporating the influence of the reset gate; the actual hidden state h_t, which is a combination of the hidden state at the previous time step h_{t-1} and the candidate activation. The closed form equations are written in (1).

$$\begin{aligned} r_t &= \sigma\left(W_{xr}x_t + W_{hr}h_{t-1} + b_r\right) \\ z_t &= \sigma\left(W_{xz}x_t + W_{hz}h_{t-1} + b_z\right) \\ \tilde{h}_t &= \tanh\left(W_{xh}x_t + W_{hh}h_{t-1} + b_h\right) \\ h_t &= \left(1 - z_t\right)\cdot h_{t-1} + z_t \cdot \tilde{h}_t \end{aligned} \tag{1}$$

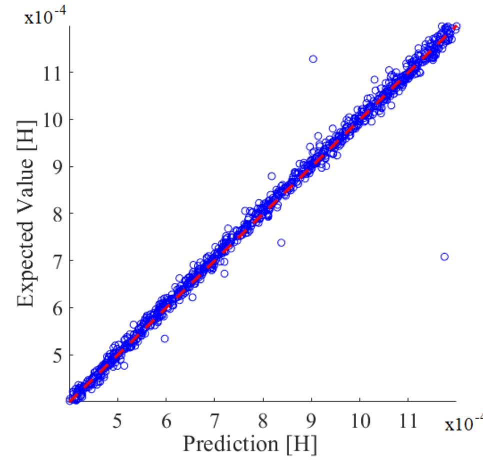
where σ is the sigmoid activation function, *tanh* is the hyperbolic tangent, W_{xr}, W_{xz}, and W_{xh} are the weights between the input x and the reset gate, the update gate, and the candidate activation respectively, W_{hr}, W_{hz}, and W_{hh} are the weights between the input h and the reset gate, the update gate, and the candidate activation respectively, and b_r, b_z, and b_h are the bias terms for the reset gate, the update gate, and the candidate activation. The dot symbol stands for the element wise product. Finally, the output layer is represented by the linear equation in (2).

$$y = W_{hy}h_t + b_y \tag{2}$$

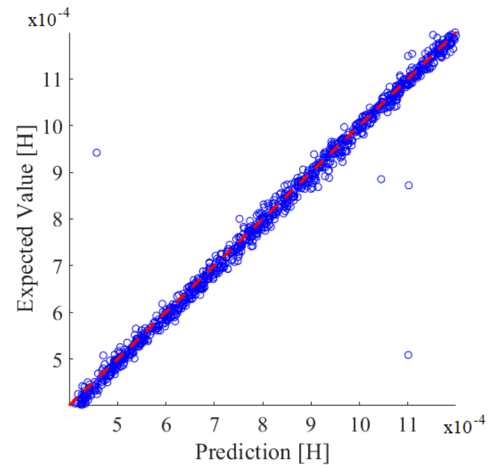
In which W_{hy} is the weight matrix between the hidden layer output and the output y of the NN and b_y is the bias term of the output layer.

IV. Results

As mentioned previously, the training has been carried out in the Matlab environment using a dataset obtained from the AC-DC converter emulated in Typhoon HIL 606, as shown in Fig. 2, randomly varying the inductances between 400μH and 1.2mH and the capacitance between 0.1mF and 2mF. The training, validation and testing have been performed using both balanced and unbalance inductance values to evaluate the goodness of the estimation in different conditions. The obtained results of the predicted values have been compared to the expected one in Fig. 4 using the scattering graph. In particular, the red dotted line represents the reference line were predicted values ideally should be to have the same value of the expected values composing the target. The blue dots, instead, represent the predicted parameter by the NN on the x-axis with respect to the expected value reported in the target on the y-axis. Respectively, in Fig. 4a is represented the inductance L_a, in Fig. 4b the inductance L_b, in Fig. 4c the inductance L_c, and in Fig. 4d the capacitance C. As it can be noticed, some outlier value is present, not corresponding the predicted value to the expected one and so being far from the red dotted line. Despite this, the majority of the test set follows the red dotted line. Therefore, it can be concluded that the passive parameter estimation method is promising. Moreover, in Table III have been reported the root mean square error (RMSE) and the mean percentage error (MPE) for each parameter.



(a)



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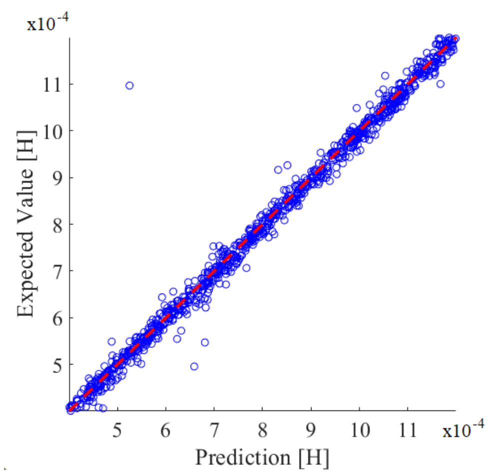

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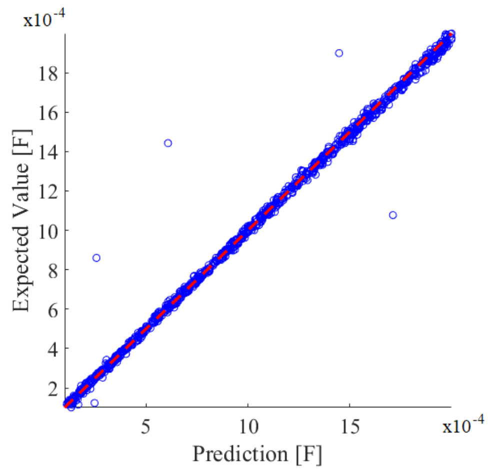

(d)

Fig. 4. Predicted parameters (blue dots) compared to the expected results (red dotted line) (a) inductance La in the range 0.4mH - 1.2mH; (b) inductance Lb in the same range; (c) inductance Lc in the same range; (d) capacitance C in the range 0.1mF - 2mF.

To further validate the proposed method for parameters identification of a boost rectifier, the Typhoon HIL 606 has been used to emulate in real-time the power converter behaviour with a time step resolution of 1µs. The control structure, data acquisition, and buffering has been implemented on the PED-Board® controller's FPGA using the LabVIEW environment. The PED-Board is based on National Instruments' sbRIO-9651 System-on-Module featuring a Xilinx Zynq7020. It enables real-time analysis by transmitting data directly to the onboard microprocessor, where the ANN closed form representation has been realized thanks to LabVIEW Real-Time. Several sets of passive parameters have been tested in the AC-DC converter to validate the NN parameters identification method. Fig. 5 shows the control panel for visualizing the sampled waveforms and the functioning of the neural network for parameter estimation. It can be noticed that in the top box the parameters of the neural network are set and the correct functioning of the algorithm is verified. At the bottom right, instead, the parameters set as targets running in the circuit emulated by the Typhoon HIL are presented and, immediately below, the parameters estimate carried out by the neural network is shown. It is clearly visible that the estimate reports the desired results, validating also the real-time application of the proposed method.

TABLE III. TRAINING OPTIONS OF THE NEURAL NETWORK

Passive Parameter	***RMSE***	***MPE***
L_a	2.075e-5	0.38%
L_b	2.950e-5	0.97%
L_c	2.561e-5	0.47%
C	4.442e-5	0.077%

V. CONCLUSIONS

In this paper a DT based identification method of passive components in a three-phase PEC has been presented. The method uses the GRU NN for estimating the three phase inductances and the DC-link capacitance. A wide dataset based on the THD of the phase currents, on the three phase currents and on the DC-link voltage waveform has been created in order to train the NN. After training, the obtained results have been illustrated using scattering graphs and RMSE and MPE values regarding the testing dataset. To validate the online real-time application of the proposed method, the NN structure have been represented in closed form and implemented on the microprocessor of the PED-Board control board. Therefore, experimental results have been carried out emulating the AC-DC converter on the Typhoon HIL 606 and running the control algorithm and the parameters identification algorithm in LabVIEW environment. The obtained results have been illustrated, validating the proposed approach and showing its feasibility.

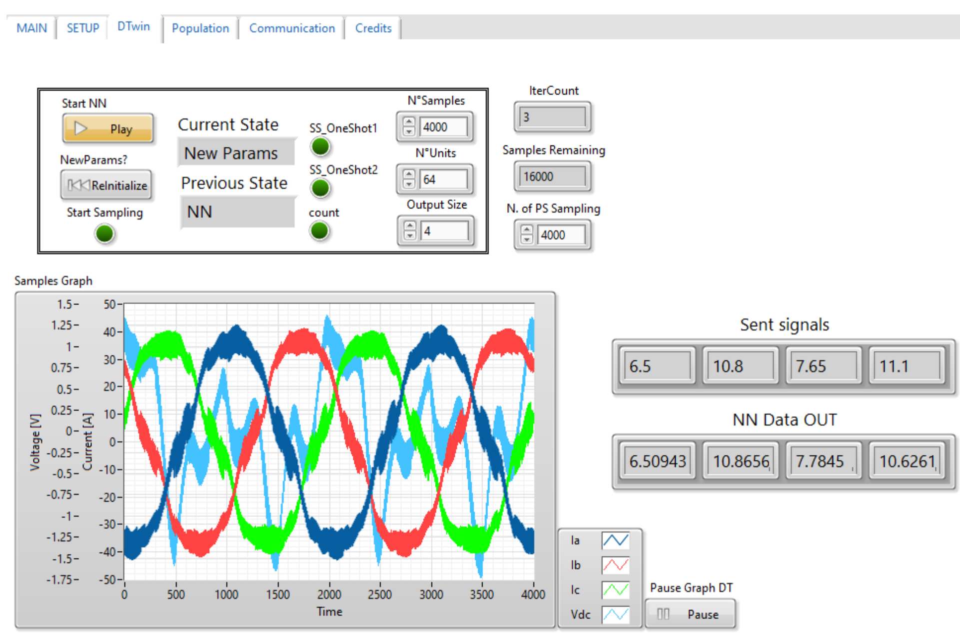

Fig. 5. Control panel in LabVIEW environment for visualizing the ANN algorithm running on the PED-board microprocessor

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REFERENCES

[1] S. Zhao, F. Blaabjerg and H. Wang, "An Overview of Artificial Intelligence Applications for Power Electronics," in IEEE Transactions on Power Electronics, vol. 36, no. 4, pp. 4633-4658, April 2021.

[2] Y. Gao, S. Wang, T. Dragicevic, P. Wheeler and P. Zanchetta, "Artificial Intelligence Techniques for Enhancing the Performance of Controllers in Power Converter-Based Systems—An Overview," in IEEE Open Journal of Industry Applications, vol. 4, pp. 366-375, 2023.

[3] F. L. d. Silva et al., "AutoTG: Reinforcement Learning-Based Symbolic Optimization for AI-Assisted Power Converter Design," in IEEE Journal of Emerging and Selected Topics in Industrial Electronics, vol. 5, no. 2, pp. 680-689, April 2024.

[4] Y. Jiang, Y. Yu and X. Peng, "Online Anomaly Detection in DC/DC Converters by Statistical Feature Estimation Using GPR and GA," in IEEE Transactions on Power Electronics, vol. 35, no. 10, pp. 10945-10957, Oct. 2020.

[5] P. Moreno, G. Laguna, J. Cipriano and A. Luna, "Detection of Abnormal Operation of PV Inverters Based on Regressive Prediction Models With Recursive Least Squares Training," in IEEE Journal of Emerging and Selected Topics in Industrial Electronics, vol. 5, no. 1, pp. 138-148, Jan. 2024.

[6] A. Vaccaro, A. Zilio and P. Magnone, "Lifetime Prediction in Power Semiconductor Devices: A Comparative study between Analytical Modeling and Artificial Neural Network," 2023 IEEE Applied Power Electronics Conference and Exposition (APEC), Orlando, FL, USA, 2023, pp. 1172-1176.

[7] Y. Fassi, V. Heiries, J. Boutet and S. Boisseau, "Toward Physics-Informed Machine-Learning-Based Predictive Maintenance for Power Converters—A Review," in IEEE Transactions on Power Electronics, vol. 39, no. 2, pp. 2692-2720, Feb. 2024.

[8] A. Nejadpak and O. A. Mohammed, "Physics-Based Optimization of EMI Performance in Frequency Modulated Switch Mode Power Converters," 2012 Sixth International Conference on Electromagnetic Field Problems and Applications, Dalian, China, 2012, pp. 1-4.

[9] A. S. Md Khalid Hasan, M. M. Hossain and H. A. Mantooth, "A Physics-based Simscape Compact SiC Power MOSFET Model with Temperature-Scaling," 2022 IEEE Energy Conversion Congress and Exposition (ECCE), Detroit, MI, USA, 2022, pp. 1-8.

[10] G. D. Nezio, M. d. Benedetto, A. Lidozzi and L. Solero, "DC-DC Boost Converters Parameters Estimation Based on Digital Twin," in IEEE Transactions on Industry Applications, vol. 59, no. 5, pp. 6232-6241, Sept.-Oct. 2023.

[11] G. Di Nezio, S. De López Diz, M. Di Benedetto, A. Lidozzi, E. J. Bueno Peña and L. Solero, "Parameters Estimation of a 3-Phase AC-DC Converter based on the Digital Twin Method," 2023 IEEE Energy Conversion Congress and Exposition (ECCE), Nashville, TN, USA, 2023, pp. 2937-2944.

[12] A. Wunderlich and E. Santi, "Digital Twin Models of Power Electronic Converters Using Dynamic Neural Networks," 2021 IEEE Applied Power Electronics Conference and Exposition (APEC), Phoenix, AZ, USA, 2021, pp. 2369-2376.

[13] H. Soliman, H. Wang and F. Blaabjerg, "Capacitance estimation for dc-link capacitors in a back-to-back converter based on Artificial Neural Network algorithm," 2016 IEEE 8th International Power Electronics and Motion Control Conference (IPEMC-ECCE Asia), Hefei, China, 2016, pp. 3682-3688.

[14] Z. She and G. Chen, "Full-Parameter Identification of BUCK Converter Based on Time-Domain Mapping Neural Network," 2022 IEEE International Power Electronics and Application Conference and Exposition (PEAC), Guangzhou,Guangdong, China, 2022, pp. 1000-1004.

[15] C. Lu, J. Li, K. Chen, W. Zhou, Q. Wu and J. Ke, "System-level Parameters Identification for DC-DC Converters Based on Artificial Neural Network Algorithm," 2023 IEEE Energy Conversion Congress and Exposition (ECCE), Nashville, TN, USA, 2023, pp. 2932-2936.

[16] Y. Lu, M. Zhang, L. Nordström and Q. Xu, "An Online Digital Twin based Health Monitoring Method for Boost Converter using Neural Network," 2023 IEEE Energy Conversion Congress and Exposition (ECCE), Nashville, TN, USA, 2023, pp. 3701-3706.

[17] S. Chen, J. Zhang, S. Wang, P. Wen and S. Zhao, "Circuit Parameter Identification of Degrading DC-DC Converters Based on Physics-informed Neural Network," 2022 Prognostics and Health Management Conference (PHM-2022 London), London, United Kingdom, 2022, pp. 260-268.

[18] S. Zhao, Y. Peng, Y. Zhang and H. Wang, "Parameter Estimation of Power Electronic Converters With Physics-Informed Machine Learning," in IEEE Transactions on Power Electronics, vol. 37, no. 10, pp. 11567-11578, Oct. 2022.

[19] Chung, Junyoung, et al. "Empirical evaluation of gated recurrent neural networks on sequence modeling." arXiv preprint arXiv:1412.3555 (2014).