Condition Monitoring of Power Electronics Converters Based on Digital Twin

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2021 IEEE 3rd International Conference on Circuits and Systems (ICCS) | 978-1-6654-1234-6/21/$31.00 ©2021 IEEE | DOI: 10.1109/ICCS52645.2021.9697303

Abstract—**This paper presents a digital twin-based condition monitoring method towards power electronic converter (PEC), which can simultaneously obtain the real-time parameters of critical components including switch, capacitor and inductor. At first, a digital simulation model of PEC is built in SIMULINK/MATLAB. Then, employ Particle Swarm Optimization (PSO) algorithm to constantly update the components' parameters in the digital model, until the simulation waveform is almost the same as that of its physical counterpart. Consequently, a digital twin imitating the actual parameter value is established for the physical PEC to realize condition monitoring. To preliminarily verify the proposed method, a simulation test on buck converter is implemented. The simulated results show that the proposed method is not only convenient, but also has high accuracy in parameter identification.**

Keywords—DC-DC power converters, condition monitoring, digital twin, parameter identification

I. Introduction

The ever increasing demand for power electronic converters in fields with high reliability requirements has resulted in concerning of condition monitoring researches. According to [1], components such as capacitances and semi-conductors may become fragile due to deterioration after long operation, resulting in failures. To improve the reliability of the power electronics, variety of condition monitoring methods are proposed to avoid catastrophic failure.

The existed condition monitoring methods can be classified into two main types, which are component-levels and system-levels. The former one monitors components individually that it can appropriately evaluate the degradation degrees of key component such as semi-conductor or capacitance [2], [3]. However, this kind of monitoring could only operate offline that the failures could not be detected in time. Moreover, the extra measuring circuits are required which leads to larger volume and costs. To detect failures timely, a real time monitoring method towards IGBT is proposed in [4]. It evaluates the health condition of IGBT by measuring the gate turn-on transient voltage. Nevertheless, the measurement error would become larger when the voltage variation caused by the increased temperature after long time operation occurs. Moreover, the extra circuits cannot be omitted either. In addition, the monitoring on single component may not be enough to indicate the health condition of the whole system.

Except for investigating the internal attribute of a single component, system-level methods could gain insight to multiple components by analyzing the overall system [5-8]. From the perspective of frequency domain [5-7], the average model could be established by injecting perturbation into the controller of the converter and analyzing the corresponding output value. Subsequently, the internal parameters of converter can be obtained through different algorithm. Nevertheless, extra signal is needed, which shows invasive to the system of interest. Moreover, methods mentioned above all use an 'average model' to characterize the basic operation of the system, which cannot show the PWM switching frequency component in the output voltage. To overcome this issue, a digital-twin-based method has been proposed in [8]. The digital twin aims to create a replica of physical converter by constantly adjusting its parameters through the algorithm to minimize difference between the waveforms of the physical converter and that of the digital counterpart. After many iterations, the values of internal parameters can be obtained without any injected signals and extra circuits. However, because linearization steps are implemented to reduce the complexity of modeling in the first place, the inevitable error between physical circuit and its digital counterpart exists. Moreover, the optimization process requires large amounts of sampled data from multiple switching period in dynamic response, which is not time-saving and simple enough.

Considering challenges of conventional methods, a new digital-twin-based method has been proposed in this paper. The parameters of the replica converter can be calculated and updated in SIMULINK/MATLAB through a totally automatically process to make the simulation waveforms approximate the actual waveforms. In addition, the process is based on time domain which avoids mathematical modeling and linearization so that no extra signal is needed and the error could be further reduced. Besides, it only needs a small amount of sampled data in one single switching period under steady state, making it simpler and quicker. Moreover, the results shows that the difference between the waveforms of digital twin and that of the physical counterpart is extremely small. Therefore, the obtained internal parameters can be used to accurately indicate the health condition of physical converter.

II. Realization of Digital Twin in Condition Monitoring

Taking the buck converter as an example, procedures of the proposed condition monitoring method is shown in Fig. 1. The digital twin aims to establish a virtual reflection of the real buck converter, so that the practical parameters of critical components can be estimated. The objective parameters include the parasitic resistances R_S, R_L, R_C of switch, inductor, capacitor, the inductance L, the capacitance C and the load resistance R. The realization of digital twin consists of two main parts: simulation layer and computation layer.

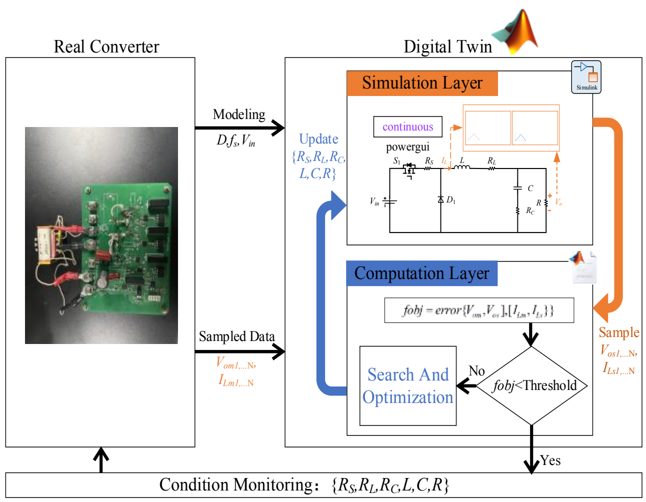


Fig. 1. Schematic diagram of the proposed digital-twin-based method

Firstly, the digital model of buck converter is built in SIMULINK which has the same duty ratio D, switching frequency f_s and input voltage V_{in} as real converter while the values of preliminary internal parameters (R_S, R_L, R_C, L, C, R) are obtained from computation layer. As simulation program is run, waveforms of output voltage $V_{oS,\mathrm{N}}$ and inductor current $I_{LS,\mathrm{N}}$ of digital twin can be observed. Then, these two waveforms are sampled to evaluate the parameter sets, which will be updated in the computation layer. It is worth noting that only ten points in one switching period under steady state condition are needed, thereby the complexity of sampling could be largely reduced.

In order to reduce the differences between $V_{oS,\mathrm{N}}$, $I_{LS,\mathrm{N}}$ of digital twin and $I_{Lm,\mathrm{N}}$, $V_{om,\mathrm{N}}$ which are sampled from physical converter, particle swarm optimization (PSO) algorithm is applied where one particle represents one parameter set. Each particle is evaluated through objective function which calculates the differences of waveforms between digital twin and its physical counterpart. Then the best one possessing the smallest error among all particles will be found. If the error is smaller than a pre-set threshold, estimated results of internal parameters will be output. Otherwise, particles will be updated and then be sent back to the simulation layer. When the number of iterations reaches its maximum or the error is smaller than the pre-set threshold, a global best particle will be obtained. The values of internal parameters corresponding to the global best particle are very close to the real values in the physical circuit thereby they can be used to indicate the health condition of the buck converter in physical world.

III. Simulation Layer and Computation Layer

A. Simulation Layer

SIMULINK is a powerful simulation tool and widely used in the field of power electronics. It is a block diagram environment, which can be used for multidomain simulation. In this paper, the simulation of buck converter based on time domain operates in SIMULINK as shown in Fig. 2, where S_1 is the MOSFET, D_1 is the diode, L is the inductor, C is the output capacitor, R is the load and R_L, R_S, R_C are respectively the parasitic resistances of the inductor L, the MOSFET S_1 and the capacitor C.

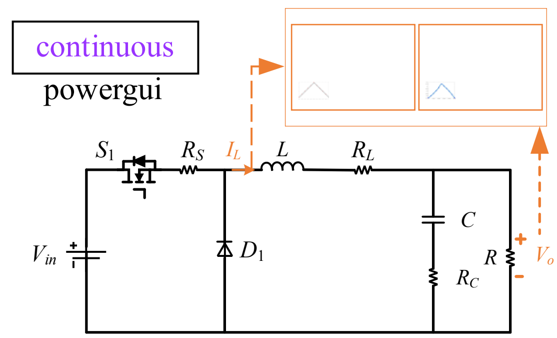


Fig. 2. Digital twin in SIMULINK

There are N sets of internal parameters $\{R_S, R_L, R_C, L, C, R\}_{1,\ldots\mathrm{N}}$ that the simulations will be conducted in SIMULINK according to every set of parameters. The update of parameters is automatically realized by the function '*sim*' of MATLAB.After the simulation process is over, 10 points would be sampled in one duty cycle under steady condition for every parameter set and then sent to computation layer.

B. Computation Layer

The computation layer aims to find a parameter set which is closer to its real value in physical converter, and degree of closeness is shown by error between waveforms calculated by objective functions. PSO algorithm is chosen in this case. It's one kind of heuristic algorithm relating to a method that encourages learners to discover solutions for themselves. It is originated from the behavior of birds flocking where the swarms search for food in a collaborative manner. To implement PSO, it's necessary to set up an objective function to evaluate the position of particles, which can determine the updated direction of particle swarms. The establishment of objective function is crucial as different weight on the error of V_o or I_L would have different effects on results, and the general form of objective function is shown in (1).

$$f_{obj} = \frac{\sum_{\mathrm{k}=1}^{\mathrm{N}} [p_1((V_{os,\mathrm{j,k}} - V_{om,\mathrm{k}})/V_{om,\mathrm{k}})^2 + p_2((I_{Ls,\mathrm{j,k}} - I_{Lm,\mathrm{k}})/I_{Lm,\mathrm{k}})^2]}{\mathrm{N}} \quad (1)$$

where output voltage $V_{om,\mathrm{k}}$ and inductor current $I_{Lm,\mathrm{k}}$ are sampled from physical converter, $V_{os,\mathrm{j,k}}$ and $I_{Ls,\mathrm{j,k}}$ are the corresponding ones sampled from the digital twin. p_1, p_2 are weighting factors, j, k are the number of particles and sampled points, respectively. N is the sample size of the measured data. In this study, N=10, which means 10 points are sampled in one single switching period under steady condition.

The procedures of PSO are shown in Fig. 3. Firstly, 100 particles are initialized and each particle represents one parameter set including L, C, R, R_L, R_S, R_C. Then each particle will be sent to simulation layer to obtain waveforms of V_{os} and I_{Ls}.

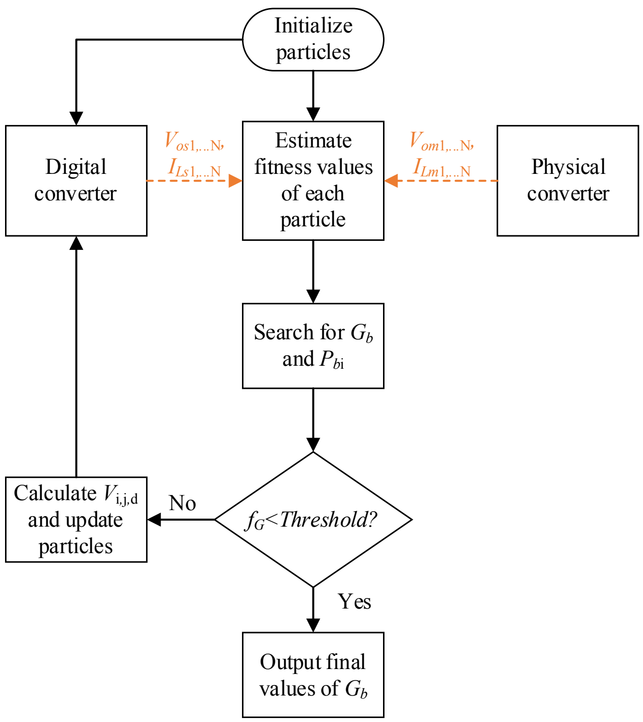


Fig. 3. Flow charts of PSO

By comparing waveforms from physical converter and digital twin, the error of every particle is calculated through the pre-set objective function. After analyzing the results, the global best particle G_b and the personal best particles $P_{b,i}$ are picked to guide the updating direction and control the updating velocity of every particle in next iteration through functions (2) and (3):

$$v_{i+1,j,d} = wv_{i,j,d} + c_1 rand(0,1)(G_{b,d} - P_{i,j,d}) + c_2 rand(0,1)(P_{b,j,d} - P_{i,j,d}) \quad (2)$$

$$P_{i+1,j,d} = P_{i,j,d} + v_{i+1,j,d} \quad (3)$$

where i is the number of iterations, j is the number of particles and d is the dimension of parameters, G_b is the global optimization so far, P_b is the individual optimization until i^{th} iteration and v is the velocity of particle. Range of each velocity have to be limited in case particles fly out of the boundary. In addition, w is the learning factor, c_1, c_2 are weighting factors which are given in advance. According to previous studies, learning factor w is related to the searching ability of global optimization and local optimization. When w is set to a relatively large value, it is more likely to find the global best position, otherwise it is easier for particles to find the local best position. In this paper learning factor w is set to 0.6. Moreover, c_1 is the social weighting factors and c_2 is the individual weighting factors that they are related to the updating direction of particle swarms. Considering the impacts of vital social experience and individual experience, c_1 and c_2 are both set to 1.5. When iteration reaches its maximum number or error of waveforms between physical circuit and digital twin is smaller than the pre-set threshold, the algorithm is terminated and the best parameter set is output. Maximum iteration times is set to 100.

IV. SIMULATION RESULTS

A. Parameters Identification

To preliminarily validate the proposed method of condition monitoring, a simulation buck converter is built in SIMULINK and its specifications are shown in Table 1.

TABLE I. STANDARD VALUES OF BUCK CONVERTER

SPECIFICATION	VALUE
Input voltage V_{in}	48V
Switching frequency f_{sw}	20kHz
Sampling rate f_{sr}	200kHz
Capacitance C	470μF
Inductance L	0.0015H
Parasitic resistances of MOSFET/L/C	0.13Ω/0.11Ω/0.08Ω
Output resistances 1/2/3	8Ω/12Ω/16Ω

The input voltage V_{in} and the switching frequency f_{sr} of digital twin should be set to the same values in the first place. In addition, Duty ratios D is given by controller. Afterwards the whole system starts operating and the parameters of digital twin are updated constantly to approach the standard values. The proximity of parameters is shown by calculated results of objective function and the degradation process of *fobj* can be seen in Fig. 4. After certain times of iterations, the value of *fobj* has already reached a relatively small value, which means the error of waveforms is very small as can be in Fig. 5. It indicates that the estimated values of parameters are very close to the standard values.

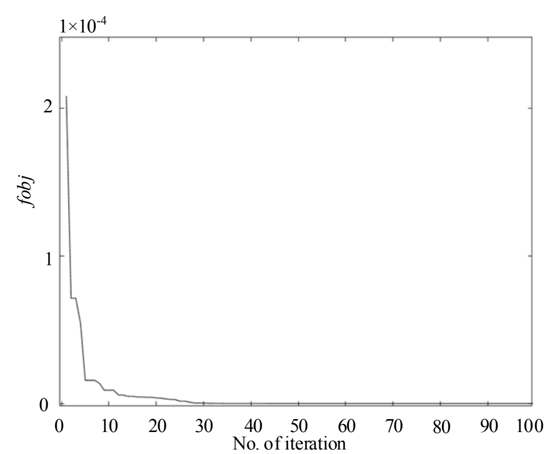


Fig. 4. Degradation process of *fobj*

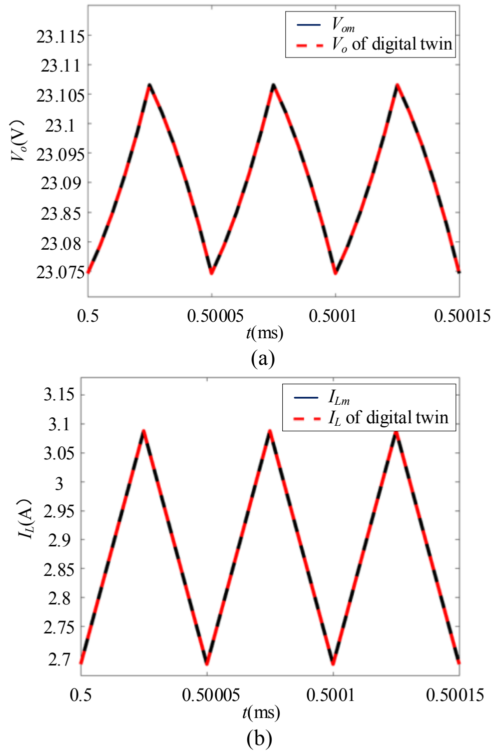
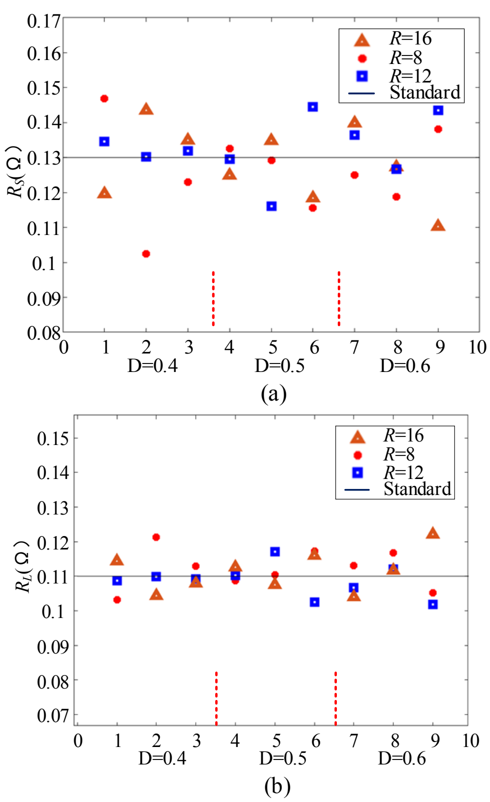


Fig. 5. Comparison of V_o and I_L

Because of the estimated accuracy of proposed method may be affected by different duty ratios and loads, tests of same parameter set have been repeated three times under different duty ratios and loads. The estimated results are presented in Fig. 6.



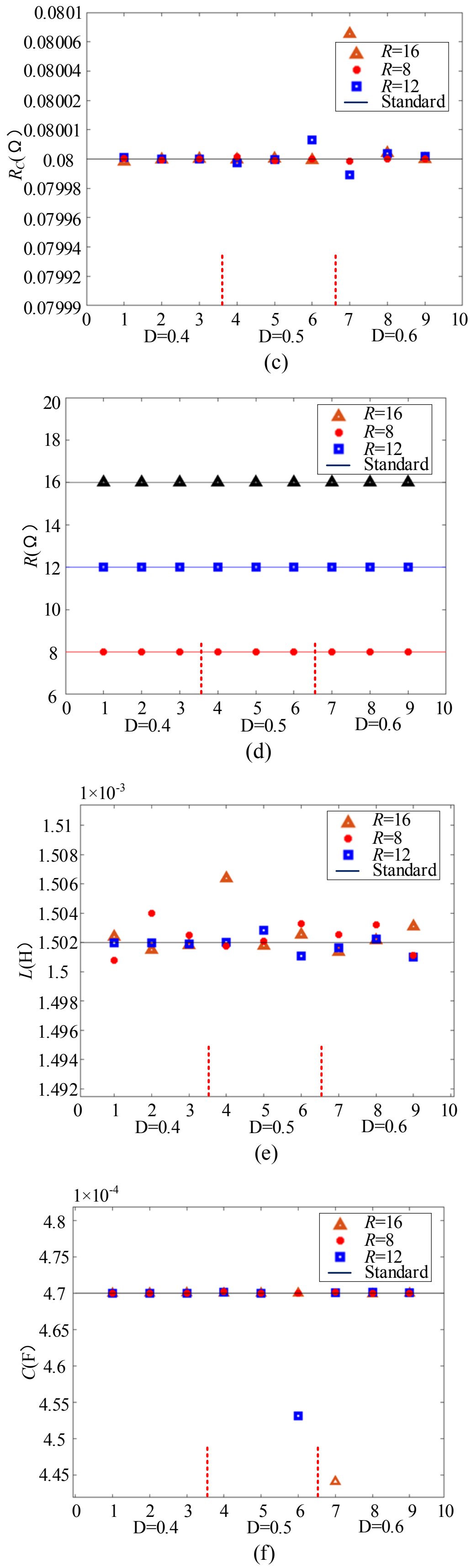


Fig. 6. Estimated results under different duty ratios and loads

Although the duty cycles and loads change all the time, the final values of L, C, R, R_C in digital twin are still very close to the standard values, which could be used to precisely monitor the health condition of critical components under different situations. In addition, the estimated results show high stability as the final results are all fluctuate within very narrow limits. Though there are a few times that the estimated results of capacitance have deviated from its standard value, it is acceptable because PSO algorithm is a heuristic method which contains a certain degree of randomness.

Moreover, the estimated results of R_L and R_S fluctuate in a small range while results of R_C is far more stable. It can be explained by the coupling of these two resistances that values different from standard values may have almost the same waveforms of V_o and I_L under different duty ratios and cannot be distinguished by objective function at present. Different from R_S and R_L, R_C directly affects the waveforms of V_o, which push particle swarms to run towards to the global optima of R_C. Though the estimated results show uncertainty of R_S and R_L, a new equivalent resistance can be defined to decoupling R_L and R_S after data analyzing, it is shown as follows:

$$R_{avg} = DR_s + R_L \tag{4}$$

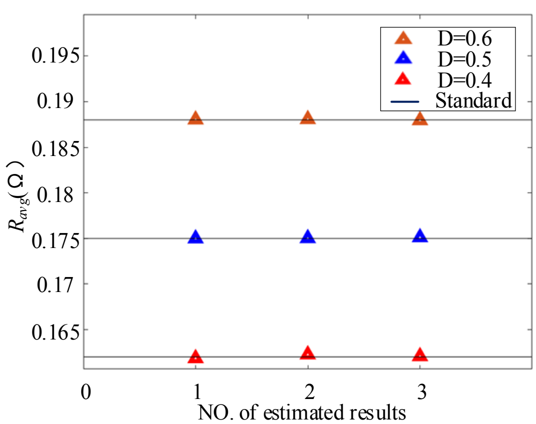


Fig. 7. R_{avg} under different duty ratios

The value of R_{avg} is D dependent value as can be seen in Fig. 7. Then R_L, R_S can be decoupling through solving functions under two different duty cycles. The finale results can be seen at Table 2:

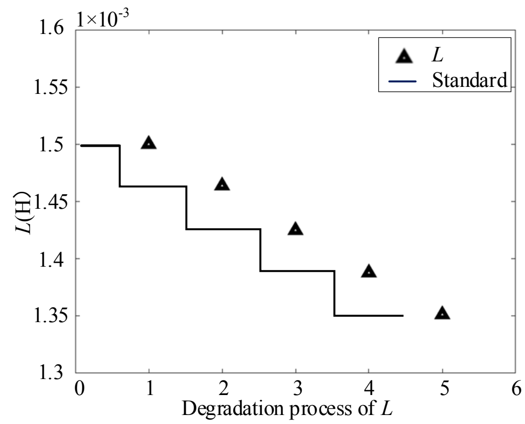
TABLE II. DECOUPLING OF R_L AND R_S

DATA	R_L	R_S
D=0.4, D=0.5	0.110135Ω	0.129831Ω
D=0.4, D=0.6	0.110133Ω	0.129805Ω
D=0.5, D=0.6	0.110136Ω	0.129812Ω

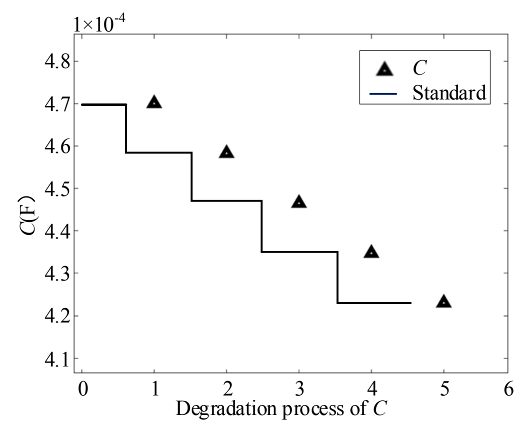
As can be seen at Table 2 the finale values of R_L, R_S are very close to the standard values as well.

B. Degradation Process of Key Components

Based on previous studies, the values of key components in a converter such as capacitance may drop by 5%-20% and the values of their parasitic resistances would increase by 20%-40% after a long-term operation. Thereby it is important to have the proposed method tested under key components' degradation process. In this study, values of capacitance and inductor drop by 2.5% each time, the value of R_C increases by 2.5% while values of R_S, R_L increase by 10% each time. The degradation process can be seen in Fig. 8.



(a)



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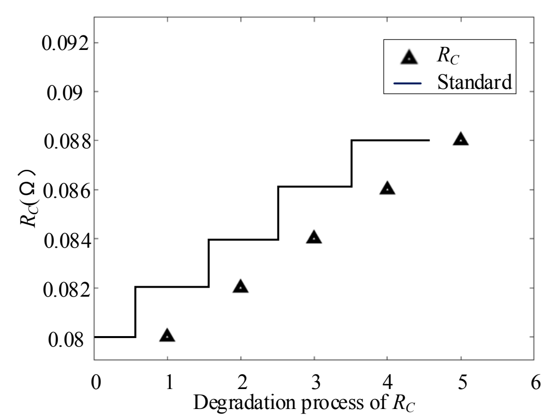

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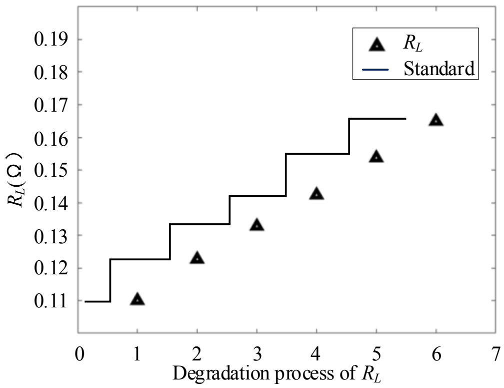
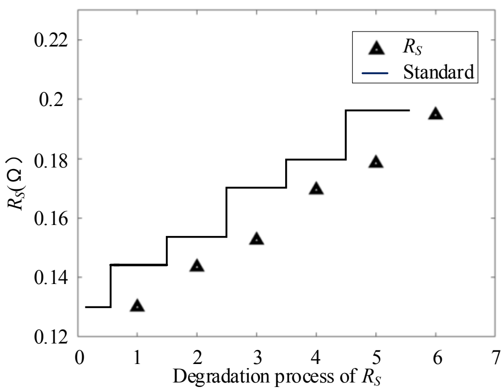


(d)



(e)

Fig. 8. Degradation process of different parameters

It has been proved that the proposed method can accurately monitor the health condition of key components even a small change has taken place.

V. CONCLUSION

This paper proposed a digital-twin-based method of condition monitoring for PEC. By building a replica of physical converter in SIMULINK, the internal parameters of the real converter could be monitored in real-time. More specifically, the internal parameters of the digital twin will be updated automatically and continuously in simulation layer and the corresponding simulation waveforms will be sampled to the computation layer. Because only ten points need to be sampled in a switching period in steady state, the complexity of implementation is reduced. Subsequently, the difference between the simulation and the real waveforms will be calculated through the objective function in computation layer. Then the PSO algorithm is applied to find a set of parameters which makes the simulation waveforms the closest to the actual ones. That set of parameters could be regarded as the real-time inter attribute of the physical converter. This process avoids tedious mathematical modeling and linearization steps so that high accuracy can be obtained. With simulation tests being conducted, the theoretical analysis has been verified that the proposed monitoring method can accurately monitor the health condition of PEC. And the experiment will be conducted later. It is worth to noting that in a more realistic situations, the accuracy of estimated results may be affected by other factors such as the temperature under different working conditions, which should be considered in future work.

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