A Novel Prognostics Scheme for Nonisolated DC-DC Converters Using Voltage Features

Zhen Jia, Zhenbao Liu, Xin Liu, Peng Zhao, Li'na Wang
School of Aeronautics
Northwestern Polytechnical University
Xi'an, China
liuzhenbao@nwpu.edu.cn

***Abstract*—DC-DC converters have been widely used in various industrial systems. Accurate performance prognostics of their remaining useful performance (RUP) can effectively avoid the occurrence of faults. This paper proposes a performance prediction method based on the output signal of the circuit, which only needs to monitor the output response of the circuit without monitoring the nodes inside the circuit. The RUP can be predicted by continuous monitoring of the output voltage. Particle filter algorithm, as one of the algorithms often employed in prediction, is found to have the biggest problem of particle degradation, which will reduce the diversity of particles and then affect the final prediction accuracy. This method monitors circuit degradation by collecting historical degradation data. In addition, the kernel smoothing algorithm is integrated into the particle filter algorithm to ensure that the particle variance unchanged with the circuit performance prediction model during the recursive propagation process. The model can be updated after obtaining new measurements. The analysis of two DC-DC converter circuits shows that the proposed prognostics scheme has good prediction accuracy for nonisolated DC-DC converters.**

Keywords-DC-DC converter; RUP prognosis; historical degradation data; particle filter

NOMENCLATURE

RUP	remaining useful performance
Voa	output average voltage
PDF	probability density function
x_k	state of k-time
y_k	observed value of k-time.
u_{k-1}	process noise sequence
w_k	measurement noise sequence
$\delta(\cdot)$	Dirac function

I. INTRODUCTION

Power supply is indispensable in industrial system, and power electronic converter is widely used in power supply equipment because of its high efficiency and flexible control. This paper considers the health monitoring of DC-DC converter, which is a common power electronic converter. DC-DC converter often fails because of its working environment, frequent variation of component tolerances and complex failure mechanisms (such as welded joints problem). Therefore, for a system with converter circuit, it is important to predict the performance of the converter circuit for its system.

Currently, the performance prediction objects of electronic systems include the whole system, individual devices (such as IGBT, transistor) and interconnect parts [1]. This paper predicts the remaining useful performance (RUP) for the complete electronic system. The RUP prediction of electronic system is based on manual method at first, then PoF method was developed, but both of them will lead to large errors. Later, PHM has emerged with the rapid development of sensing and communication technologies. PHM aims to determine the occurrence of failure, reduce system risk and trigger early maintenance task [2]. Some literatures have introduced the PHM implementation scheme of electronic products [3,4]. Considering that the internal signal of the electronic system is not easy to access, this paper chooses to monitor only the output signal of the circuit, and tries to analyze the degradation trend of the system from the output signal. RUP prognostics is based on predicting the changing trend of indicative life characteristics. Firstly, the typical features of electronic system are extracted and correlated with the performance of the system. Therefore, the RUP prognostics is transformed into the prediction of the trend of the specified characteristic over time.

At present, the main prediction method used is particle filter (PF) [10]. Some studies applied other algorithms to predict the trend (such as SVM [1], PSO-NGM [5]). PF is a common method for predicting RUP [6] of systems because of its advantages in dealing with non-linear problems. There are unknown parameters in its state space model. However, the PF-based method is prone to particle degeneracy, in which the weight of most particles can be neglected after several iterations. In order to avoid particle degeneracy, resampling method is often used, but because resampling scheme can reduce the diversity of particles, particle dilution will occur. These shortcomings may lead to large errors in RUP estimation of nonisolated DC-DC converter circuits. In addition, because PF-based method can only process a fixed number of samples in the whole filtering time, bear a large computational load, which leads to low computational efficiency and is not suitable for real-time system prediction target.

In this paper, a new prediction model based on particle filter is proposed for RUP prediction of DC-DC converter

This work was sponsored by the Natural Science Foundation of China under Grant 61672430.

978-1-7281-0860-5/19/$31.00 ©2019 IEEE

circuits. The key of the proposed framework is to use the resampling propagation strategy of reverse PF process. The existing measurement information is effectively utilized to avoid particle decay, thus reducing the error of RUP estimation. The framework has the ability to adjust the number of particles dynamically and adaptively, which can improve the online efficiency by reducing the running time of the algorithm. In this proposed method, the parameters of the prediction model, which are considered as part of the joint state, can be transmitted in real state. In addition, the kernel smoothing algorithm is integrated into the particle filter algorithm to ensure that the particle variance unchanged with the circuit performance prediction model during the recursive propagation process. The model can be updated after obtaining new measurements. Therefore, the proposed framework is suitable for online applications. Fig.1 depicts the flowchart of the method.

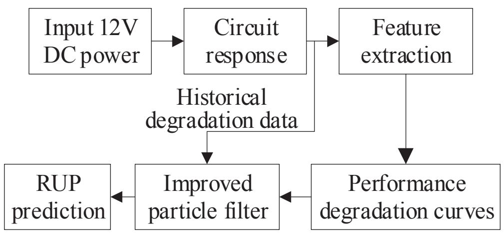


Figure 1. Flowchart of the proposed prognostics scheme for DC-DC converters

The rest of this paper is organized as follows. Section II introduces the development of fault prediction. Two case studies and experimental results are presented in section III. Section IV summarizes the conclusions.

II. FAILURE PROGNOSTICS

The degradation failure of components is a cumulative result. In the process of DC-DC converter circuit rising from normal state to complete failure, output average voltage (Voa) changes from rated value to threshold value. According to the definition of circuit designer, RUP is defined as useful performance from now on until the performance is completely lost. When the circuit does not work for the whole system, it means that the life of the circuit will be terminated (for example, the operation of the system will be terminated if the output voltage is too high). The key characteristics of continuous monitoring circuit response (Voa selected in this paper) can form performance degradation curve. The prediction of RUP can be achieved by tracking the downward trend of the performance degradation curve.

The RUP can be evaluated by measuring the performance degradation data of the object and converting the degradation data into observations and updates. Statistical prediction is the most commonly used method for estimating RUP. Given the trend of performance degradation, there are some non-linear and non-Gaussian methods for real-time estimation of RUP in the existing literature. For example, a Monte Carlo method, sequential importance sampling, can calculate the probability density function (PDF) of parameters in a nonlinear model. PF is considered as Monte Carlo approximation of Bayesian estimation, and it is now often used as a method in the field of prediction. The generation of resampling concept makes the particle degradation problem overcome. In this paper, an improved RUP prediction method based on PF theory is proposed. This method takes full account of the historical degradation experience collected before and converts it into valuable information to improve robustness and accuracy.

The state model of a dynamic system consists of a non-linear state equation f and a measurement equation h, which are expressed as follows:

$$x_k = f_k(x_{k-1}, u_{k-1}) \tag{1}$$

$$y_k = h_k(x_k, w_k) \tag{2}$$

where x_k represents the state of k-time and y_k represents the observed value of k-time. u_{k-1} and w_k represent process noise sequence and measurement noise sequence respectively. Both of them are independent and identical distributed (i.i.d.). When the posterior probability density function (PDF) $p(x_{k-1} \;/\; y_{1:k-1})$ at time k-1 is known in the predicting phase,, the calculation method of the prior PDF is as (3). In the update phase, the posterior PDF can be calculated by (4) when the measured value y_k is obtained.

$$p(x_k | y_{1:k-1}) = \int p(x_k | x_{k-1}) p(x_{k-1} | y_{1:k-1}) dx_{k-1} \tag{3}$$

$$p(x_k | y_{1:k}) = \frac{p(y_k | x_k) p(x_k | y_{1:k-1})}{\int p(y_k | x_k) p(x_k | y_{1:k-1}) dx_k} \tag{4}$$

Iteration between the two formulas is the optimal Bayesian evaluation.

A. Particle Filter

In the field of PHM, the role of particle filter is to approximate the non-linear filter. A posterior PDF can be expressed as

$$p(x_{0:k} | y_{1:k}) \approx \frac{1}{N} \sum_{i=1}^{N} \delta(x_{0:k} - x_{0:k}^i) \tag{5}$$

where $\{x_{0:k}^1, x_{0:k}^2, x_{0:k}^3, \ldots, x_{0:k}^N\}$ is a set of independent and identically distributed state samples and $\delta(\cdot)$ is a Dirac function. However, it is usually sampled from an easy-to-use distribution instead of from a posterior PDF. A posterior PDF can then be evaluated using the following methods:

$$p(x_{0:k} | y_{1:k}) \approx \sum_{i=1}^{N} \bar{w}_k^i \delta(x_{0:k} - x_{0:k}^i) \tag{6}$$

$$\bar{w}_k^i = \frac{w_k^i}{\sum_{j=1}^{N} w_k^j}$$

$$w_k^i = \frac{p(y_{1:k} | x_{0:k}^i) p(x_{0:k}^i)}{q(x_{0:k}^i | y_{1:k})} = w_{k-1}^i \frac{p(y_k | x_k^i) p(x_k^i | x_{k-1}^i)}{q(x_k^i | x_{k-1}^i, y_{1:k})} \tag{7}$$

The evaluation state x at time k is:

$$\overline{x}_k = \sum_{i=1}^{N} \overline{w}_k^i x_k^i \tag{8}$$

B. The Proposed Method

The new improved particle filter algorithm proposed in this paper takes into account the historical degradation data, because the historical data will inevitably be subject to various disturbances. The interference is realized by changing the parameters of the device in its tolerance. Obtain a certain number of historical degradation data for use. Under the supervision of these historical degradation data, the evaluation effect will be improved. The specific implementation methods are as follows.

According to the Monte Carlo method, the posterior distribution approximates the weight of N samples extracted from the posterior distribution, which is expressed as:

$$p(x_k | y_{1:k}, Y_{exem1:k}) \approx \frac{1}{N} \sum_{i=1}^{N} \delta(x_{0:k} - x_{0:k}^i) \tag{9}$$

where Y_{exem} is the mean of different curves formed by setting historical data collected in different environments. $Y_{exem1:k}$ represents known historical data values from time 1 to k. It can be seen that the data $y_{1:k}$ running in real time is different from those prepared data. A posterior PDF under the supervision of historical data can be evaluated by the following formula:

$$p(x_{0:k} | y_{1:k}, Y_{exem1:k}) \approx \sum_{i=1}^{N} \overline{w}_k^i \delta(x_{0:k} - x_{0:k}^i) \tag{10}$$

$$\overline{w}_k^i = \frac{w_k^i}{\sum_{j=1}^{N} w_k^j}$$

$$\begin{aligned} w_k &= \frac{p(y_{1:k} | x_{0:k}, Y_{exem1:k}) p(x_{0:k} | Y_{exem1:k})}{q(x_{0:k} | y_{1:k}, Y_{exem1:k})} \\ &= w_{k-1} \frac{p(y_k | x_k, Y_{exem1:k}) p(x_k | x_{k-1}, Y_{exem1:k})}{q(x_k | x_{0:k-1}, y_{1:k}, Y_{exem1:k})} \end{aligned} \tag{11}$$

The weight of each particle is:

$$w_k^i = w_{k-1}^i \frac{p(y_k | x_k^i, Y_{exem1:k}) p(x_k^i | x_{k-1}^i, Y_{exem1:k})}{q(x_k^i | x_{0:k-1}^i, y_{1:k}, Y_{exem1:k})} \tag{12}$$

Make the following assumptions:

$$p(x_k^i | x_{k-1}^i, Y_{exem1:k}) = p(x_k^i | x_{k-1}^i) \tag{13}$$

$$q(x_k^i | x_{0:k-1}^i, y_{1:k}, Y_{exem1:k}) = p(x_k^i | x_{k-1}^i) \tag{14}$$

According to this assumption, (12) equals:

$$w_k^i = w_{k-1}^i p(y_k | x_k^i, Y_{exem1:k}) \tag{15}$$

It can be seen from (15) that in the updating phase, when calculating the particle weight, not only the current degraded filtering data, but also the historical degraded data under interference conditions are taken into account.

The distribution of each parameter for multiple parameters can be approximated by the following equation:

$$p(p_k | y_{0:k}) \approx \sum_{i=1}^{N} w_k^i N(p_k | m_{k-1}^i, h^2 V(p_{k-1})) \tag{16}$$

where h is the smoothing factor, $0 < h < 1$.

Then parameter particles at time k is:

$$p_k^i \sim N(p_k | m_{k-1}^i, h^2 V(p_{k-1})) \tag{17}$$

In (16) and (17), $N(\bullet)$ is the Gaussian kernel distribution, $V(p_{k-1})$ is the variance of parameter particles at time $k-1$. For an unknown parameter, the recursive form is constructed now.

The state of k-cycle is obtained as follows:

$$\overline{x}_k = \sum_{i=1}^{N} \overline{w}_k^i x_k^i \tag{18}$$

III. EXPERIMENT

A. Experimental Setup

Two DC-DC converter circuits are selected, one is DC-DC converter based on MC34063a and the other is DC-DC converter based on TL494, to verify the proposed RUP prognostics method. SPICE models and real circuits are established respectively. The two circuit diagrams are shown in Fig. 2 and Fig. 3 respectively. The experimental environment of real circuit includes power supply, digital oscilloscope, two test DC-DC converter circuits, a data acquisition board of National Instruments, and LabVIEW software for recording collected data. The input of the two converter circuits is 12V DC power supply.

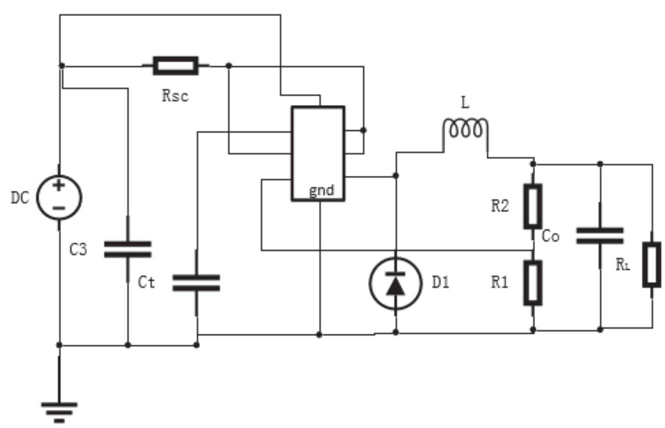


Figure 2. DC-DC converter circuit schematic based on MC34063a

The experiment was carried out in the presence of component tolerance. Definitions of tolerances and faults need to be defined in advance. Different from the existing definition of them, the parameters of key components deviate from their rated values to a certain extent. This paper considers this issue from a new perspective of Voa when the circuit works stably. The goal of a DC-DC converter circuit is to provide a constant output voltage, so the Voa of this circuit is of the greatest concern to the user. The output voltage of the two test converters is both 5V, and the allowable deviation of the output voltage is 5%. Therefore, we define that if the Voa deviation exceeds the tolerance range of 5%, the converter circuit is considered to be faulty; if the Voa exceeds the pre-defined fault threshold (e.g., deviates from its nominal value by 20%), the converter circuit will reach complete failure. The threshold is defined according to the functional loss of the converter.

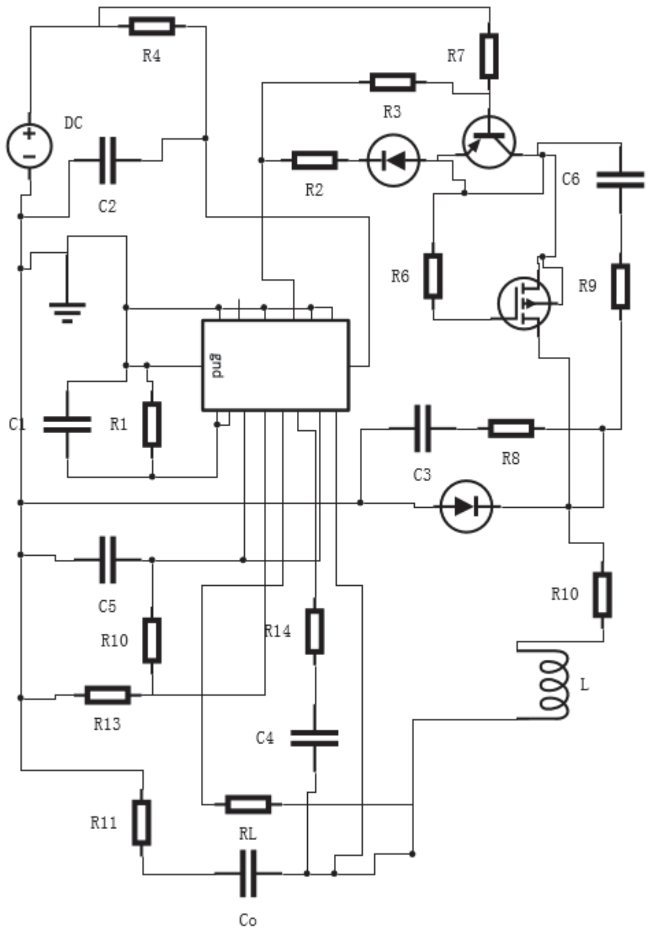


Figure 3. DC-DC converter circuit schematic based on TL494

B. Fault Classes

Several highly sensitive components are selected for each circuit to produce circuit degradation. The circuit of DC-DC converter based on MC34063A determines that the sensitive elements are R1, R2, Ct and Rsc, while the DC-DC converter circuit based on TL494 chooses L1, R11, R12 and R13. These sensitive components are determined by the analysis of circuit principles. One or two degradation categories are defined for each sensitive component. The DC-DC converter circuit based on MC34063a has six fault levels and one fault-free level. The DC-DC converter circuit based on TL494 has five fault levels and one fault-free level. In order to validate the proposed recognition method, in each class, the values of sensitive components are set manually in uncertain intervals based on the simulation results of Saber software. When Voa changes from 5% to 25%, the fault value is obtained. Table I shows the fault values set in the two converter circuits, respectively.

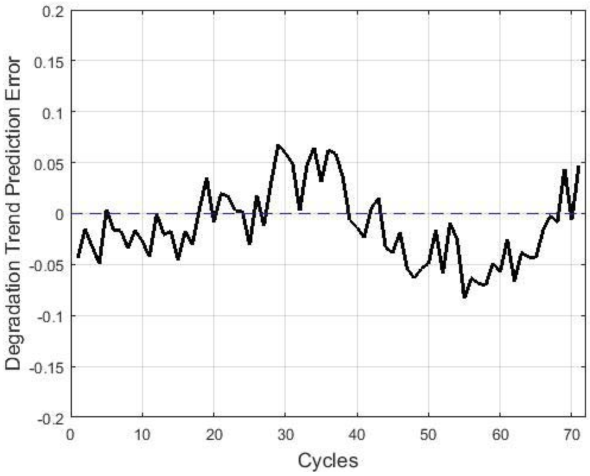
TABLE I. FAULT CLASSES FOR TWO TEST CONVERTERS

Fault Code	**DC-DC Converter based on MC34063a**		
	Fault class	***Nominal value***	***Faulty value***
F0	NF	-	-
F1	R1↑	1kΩ	1.07,1.1,1.14,1.18,1,22,1.25,1.28, 1.33,1.39,1.44,1.5kΩ
F2	R1↓	1kΩ	0.75,0.764,0.776,0.81,0.82,0.83k, 0.843,0.869,0.911,0.926,0.937kΩ
F3	R2↑	3kΩ	3.2,3.267,3.326,3.466,3.533,3.6, 3.667,3.733, 3.866,3.933,4kΩ
F4	R2↓	3kΩ	2,2.067,2.133,2.266,2.333,2.4, 2.467, 2.533,2.667,2.733,2.8kΩ
F5	Rsc↑	3kΩ	0.324,0.33,0.336,0.347,0.353,0.358, 0.369,0.381, 0.401,0.41,0.416Ω
F6	Ct↑	379pF	9.94,12.27,14.46,18.61,20.24,21.97, 24.94,27.89, 31.95,33.06,34.2nF
	DC-DC Converter based on TL494		
F7	NF	-	-
F8	L↓	5mH	0.186,0.147,0.095,0.071,0.062,0.05 7,0.044,0.031,0.027,0.022,0.018mH
F9	R11↑	10mΩ	38,178,246,346,392,414,415,146, 417.5,417.8,418mΩ
F10	R12↑	15kΩ	20.13,20.24,20.31,20.61,20.76,20.8 8,20.93,20.95,21.03,21.22,21.33kΩ
F11	R12↓	15kΩ	0.31,0.35,0.37,0.384,0.393,0.4,0.42, 0.44,0.46,0.48,0.49kΩ
F12	R13↓	10Ω	7.03,7.12,7.18,7.21,7.23,7.24,7.31, 7.35, 7.40,7.42,7.43Ω

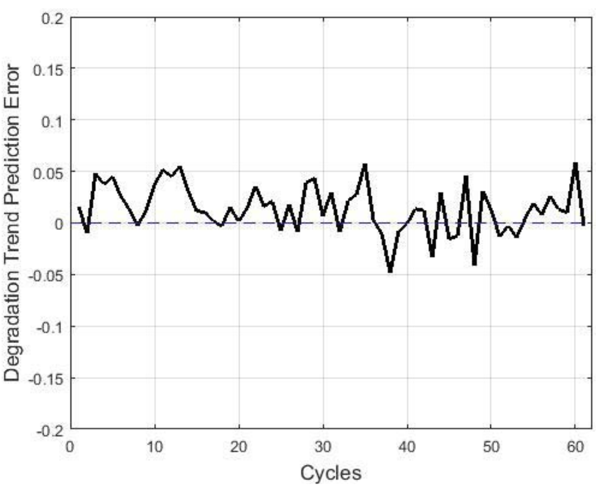
For each degradation situation, corresponding Voa curves or so-called performance degradation curves can be created to represent different performance states of the circuit. Each of them consists of three parts: normal section within tolerance, increasing section within fault threshold, increasing section outside fault threshold or normal section within tolerance, decreasing section within fault threshold and decreasing section. Because the working principle of DC-DC converter circuit is complex, it is difficult to express the relationship between component value and performance clearly by formula. Voa curve can be regarded as a function of sensitive elements, in which the parameters of sensitive components are independent variables and the output response of circuit Voa is dependent variables.

C. Degradation Analysis

RUP refers to the residual cycle from the beginning of the prognostic module cycle to the EOP cycle. When abnormalities are detected, the prognostic module is triggered immediately. The predicted RUP value of the proposed filtering method is compared with the actual RUP value, which shows the predictive ability of the developed prediction method. Obviously, the expected prediction error is zero. Assume that the failure level of each component increases (or decreases) over time. It is assumed that when Voa deviates from nominal value by more than 20%, i.e., 4V or 6V, the circuit will reach complete failure. For example, according to the above fault threshold setting, for component R13 of DC-DC converter based on TL494, circuit fails refers to the Voa value exceeding 4V or 6V. For the two DC-DC converters used in this experiment, the nominal output voltage is 5V, and the two thresholds 4V and 6V correspond to different sensitive components in different converter circuits.



(a)



(b)

Figure 4. RUP prediction error for (a) Ct and (b) R1↑ in DC-DC converter based on MC34063a.

Once the prediction module is triggered, the fault indication value Voa is monitored in real time and tracked at any period to predict RUP. The prognostic results of Ct and R1 ↑ of DC-DC converter based on MC34063a and R12 ↓ and R12 ↑ of DC-DC converter based on TL494 are separately shown in Figs. 4 and 5. The black line in the figures represents the measured value, the green line refers to the tracking value, the red line refers to the predicted value, and the blue dotted line is the failure threshold. It can be seen from these figures that the trend of tracking and forecasting is closely related to the true value before reaching the failure threshold. Moreover, the error between the real fault cycle and the predicted EOP is small. Experiments show that the predicted degradation trend can well track the real degradation trend for the two tested DC-DC converter circuits. The Fig. 4 (a) and (b) are respectively the deterioration trend prediction errors of component ct faulty case in the first buck circuit and the value of R1 increasing faulty case. The degradation trend prediction error of R12 increasing faulty case in the second DC-DC converter circuit is shown in Fig. 5. The RUP of the circuit can be estimated relatively accurately. The prediction curve is in good agreement with the actual curve, which further verifies the accuracy of the prediction. The relative smoothing of the estimated curve proves that the prediction method is robust when the prediction module is started.

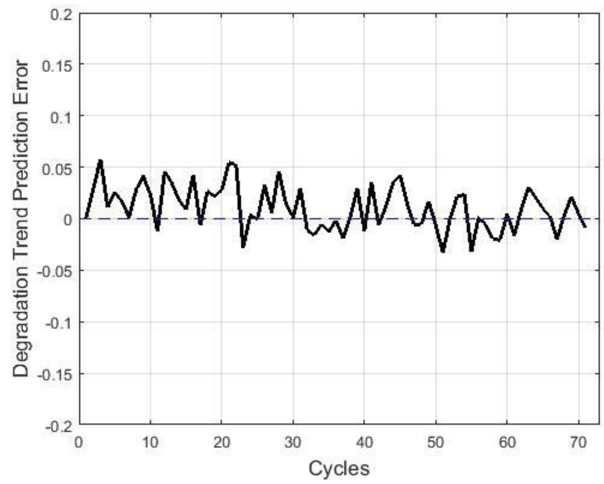


Figure 5. RUP prediction error for R12↑ in DC-DC converter based on TL494.

IV. CONCLUSION

In this paper, an improved remaining useful performance prediction scheme for nonisolated DC-DC converter circuits is developed to provide early performance prediction in order to avoid catastrophic system failures of electronic systems. Compared with the method based on circuit node equation, the developed method only needs to monitor the response of the stimulated circuit at the output node, which provides efficient performance analysis for the converter circuit. The proposed prognostics method based on improved particle filter fully considers historical degradation data as a precedent for more accurate prediction of RUP. Two cases verify the effectiveness of the developed prediction method. It shows that the RUP estimates at different time are close to linear, and relatively accurate prediction is achieved. This method is helpful for preventive maintenance and avoiding unplanned downtime of the system.

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