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A prognostic methodology for power MOSFETs under thermal stress using echo state network and particle filter

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ABSTRACT

Reinforcing the reliability of power semiconductor devices is crucial for extending the lifetime of the power-converter based electrical systems. This paper aims at developing a novel prognostics methodology for estimating the Remaining Useful Life (RUL) of the power Metal-Oxide Field-Effect Transistors (MOSFETs). The variation of on-state resistance as an important fault indicator under thermal overstress is utilized as the main database. A recently proposed neural network paradigm, namely Echo State Network (ESN) is utilized here to derive a degradation model, taking into account its high efficiency in modeling nonlinear dynamical systems. Meanwhile, a particle filter approach is developed to update the initially trained ESN model and to quantify the uncertainty of the RUL prediction online. The accuracy and efficiency of the proposed prognostic methodology has been verified based on an accelerated aging experimental dataset.

1. Introduction

The reliability of power converters plays an important role in extending the lifetime of electrical systems, such as electrical vehicles, wind generation systems, photovoltaic systems, helicopters, etc. As indicated in the literature and historic data, power semiconductor devices, principally insulated gate bipolar transistors (IGBTs) and metal-oxide field-effect transistors (MOSFETs), exceed the other components of a power converter as main components susceptible to failure [1–3].

Until very recently, the importance of prognostic is realized by the industry. Electronic and electric devices can fail instantly without any prior indication of failure. It is extremely dangerous for mission critical systems. Different from fault diagnosis that focus on instantaneous failures, the main purpose of prognostic is to estimate the remaining useful life (RUL) and its corresponding confidence interval of a system before a failure occurs [4, 5]. It is thereby an important procedure to plan a condition-based maintenance. In this sense, the instrument availability can be improved, and cost reduction can be realized [6].

Two essential types of prognostic methods can be divided, namely model-based and data-driven methods. Model-based methods rely on a mathematical or/and analytical model to describe the degradation of the target system. Whereas data-driven methods assume that the statistical characteristics of the experimental data are relatively unchanged until a malfunction occurs [7]. Only a few studies have been done on estimating the RUL of power semiconductors. In [8, 9], strain-based models based on the junction temperature information were developed to estimate the number of cycles to failure under given junction temperature swing amplitude. In [10], a data-driven method was developed based on relevance vector machine and the degradation data. In [11], Kalman and Particle filters were proposed for prognosis. Nevertheless, not much detail was provided. From the recorded run-to-failure data, the lifetimes and degradation behaviors in different tests vary in a wide range. Considering this variation, high generalization capability of the prognostic model is required. The degradation of power semiconductor is highly dependent on the usage which is usually unknown in prior. The prognostic model should be self-adaptable in different usages.

In this paper, a prognostic approach is proposed to estimate the RUL of MOSFETs by taking on-state resistance as the health indicator. In this approach, a recently proposed neural network paradigm, namely Echo State Network (ESN), thanks to its high performance on nonlinear modeling, is adopted to model the on-state resistance evolution. In addition, particle filter is combined to the ESN model to realize self-adaptation and uncertainty evaluation.

The rest of paper is organized as follows: Section 2 is dedicated to presenting the proposed prognostic approach, including the principle and implementing procedure, the ESN based prediction and particle filter based adaptation. Following that, the test results are

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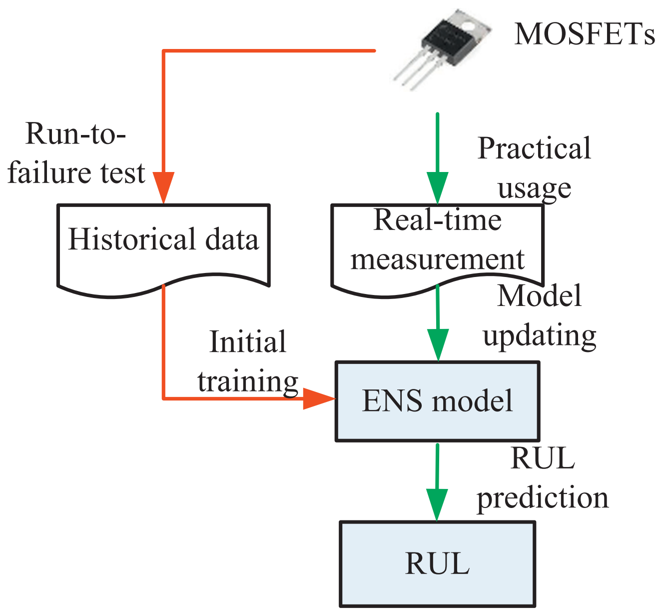

Fig. 1. Flowchart of the prognostics approach.

demonstrated in Section 3. Two types of test are carried out on different datasets. The results are also discussed in the same section. Finally, Section 4 concludes this study.

2. ESN based prognostic methodology

2.1. Principle

As shown in Fig. 1, the framework of the proposed approach can be divided into offline stage (red arrow path) and online stage (green arrow path).

In the offline stage, the ESN based prognostics model is trained by feeding the historical run-to-failure data. In the online phase, the initial prognostic model can be updated by online measurements thanks to the application of particle filter. With the updated model, the RUL prediction can be realized in real-time.

2.2. ESN based prognostic model

From different run-to-failure tests, it has been found that the mechanisms of semiconductor degradation are so complex that it is hard, if not impossible, to establish an analytical and physical degradation model and perform model-based prognostics. Data-driven prognostics is therefore more relevant in this case. In this paper, a recently converging self-cognizant data-driven prognosis model, named ESN and known as an alternative branch of Recurrent Neuron Networks (RNNs) is used to model the evolution behavior of the on-state resistance.

ESN consists of a non-trainable recurrent part (reservoir) and a simple linear readout. Compared with the conventional RNNs structure, ESN can be trained much faster without the risk of local minima. In addition, the vanishing problem in classical RNNs can be avoided naturally in ESN. This makes ESN suitable to handle long-term dependency time series, in which scope prognostics is a typical case.

As shown in Fig. 2, the state updating of a typical structure follows

$$\tilde{x}(k) = \tanh(W^{in}[1;u(k)] + Wx(k-1))$$
$$x(k) = (1-\alpha)x(k-1) + \alpha\tilde{x}(k) \tag{1}$$

where $u(k)$is the input vector, $x(k)$ is the neurons' state, $\tilde{x}(k)$ is its update at time step k. W^{in} and W are respectively the input matrix and recurrent matrix. $\alpha \in (0,1]$ is the leakage rate.

The output is defined as the linear combination of inputs and

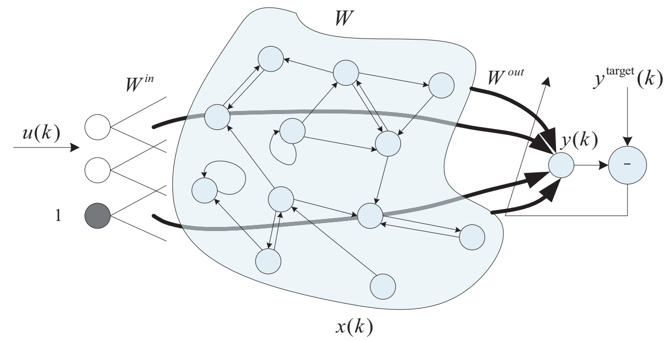

Fig. 2. Graphic illustration of ESN principle.

current states, as

$$y(k) = W^{out}[1;u(k);x(k)] \tag{2}$$

where $y(k)$is output vector, and W^{out} is the output matrix.

To realize ESN, the number of neurons should be set firstly according to the memory size requirement. The input matrix W^{in} and the recurrent matrix W are initialized normally randomly instead of a complex training in classical RNNs. The leakage rate α is another parameter to be initialized. A practical configuration of an ESN is summarized in [12]. As W^{in}, W, α are parameterized, the state subject to one input series can be calculated. The output matrix W^{out} can then be calculated through a linear regression (see details in [12]).

2.3. Particle filter for ESN updating

As the degradation of power semiconductor is affected by several factors, the prognostic model should be self-adaptive in the whole lifecycle. In this study, particle filter is used to update the initially trained ESN prognostic model and to quantify the uncertainty of the RUL prediction online. Notice that, the output matrix W^{out} is updated in our case.

Particle filter is a technique for implementing a recursive Bayesian filter by Monte Carlo simulations. The key idea is to calculate posterior density function by a set of random samples with associated weights.

Denoting P particles at time k as $\{W_i^{out}(k) | i = 1, \cdots, P\}$, the weight of $W_i^{out}(k)$ is $\omega_i(k)$. The evolution model of $W_i^{out}(k)$ can be expressed as

$$W_i^{out}(k) = W_i^{out}(k-1) + w(k) \tag{3}$$

where $w(k) \sim N(0, \sigma_p)$. The weights can be updated as [13].

$$\omega_i(k) = \omega_i(k-1)p(y(k) \mid x_i(k)) \tag{4}$$

where $p(y(k)|x_i(k))$ is the likelihood function, which is usually distributed normally, as

$$p(y(k) \mid x_i(k)) = f(y(k) \mid y_i(k), \sigma_L) \tag{5}$$

where the distribution centre is the estimated output $y_i(k)$ and the standard variance σ_L is a preset parameter.

The implementing procedure of particle filter can be summarized as Algorithm 1.

Algorithm 1. Online adaptation of output matrix by particle filter.

Input: $u(1), \ldots, u(Nc)$; $y(1), \ldots, y(Nc)$

Step1: Initialize $\{W_i^{out}(0) | i = 1, \cdots, P\}$, $\{\omega_i(0) | i = 1, \cdots, P\}$, $\{x_i(0) | i = 1, \cdots, P\}$, σ_L, σ_P.

for $k = 1$: Nc.

Step2: Calculate $x_i(k)$, $(i = 1, \ldots, P)$ according to Eq. 1.

Step3: Predict $W_i^{out}(k)$ according to Eq. 3.

Step4: Predict $y_i(k)$ according to Eq. 2.

Step5: Calculate likelihood $p(y(k)|x_i(k))$ according to Eq. 5.

Step5: Update $\{\omega_i(k) | i = 1, \cdots, P\}$ according to Eq. 4.

Step6: Normalize weight.