Online Optimization of Degradation-based Burn-in Using Convolutional Neural Network

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1. Introduction

With increasing market competition, reliability has been regarded as one of the important quality indicators for modern products and exerts great effects on product price and manufacturer reputation. Therefore, manufacturers have great impulsion to design and produce products with high reliability to maintain market competitiveness. Burn-in has been proven to be one effective and low-cost means to identify weak units and improve products' onsite reliability from the customer's perspective.

At present, various methods based on random degradation models have been proposed [1-3]. These methods obtain the optimal strategy by modeling degradation data and minimizing cost functions. However, there are some problems with these methods. Firstly, establishing the physical model to describe the degradation trend depends on fully understanding the failure mechanism of products, which is usually quite difficult and unavailable. Secondly, burn-in scheme is made offline, and the degradation measurement in burn-in test is not employed. Additionally, the effectiveness of burn-in strategies is challenged by the correctness of some prior information. Inaccurate information and unreasonable settings will seriously impact the burn-in effect.

In degradation-based burn-in test, a long test duration could improve the burn-in effect but increases the test cost and vice versa. Furthermore, burn-in test will also increase the degradation level, thereby decreasing the remaining useful lifetime in field use. Hence, the test duration should be regarded as an essential factor in the burn-in scheme.

In this paper, we attempt to solve problems stated above with a new method which mainly contains two phases. During the offline training phase, CNN1 is combined with our sliding window strategy to build the relationship between degradation trend and measured data, and here a well-trained CNN1 will be obtained to conduct the screening task. Then, combine the well-trained CNN1 with our group-accuracy strategy, and the optima burn-in time will be obtained. During Online testing phase, through the proposed online optimization algorithm, the actual burn-in time of products to be screened will be adjusted and the t

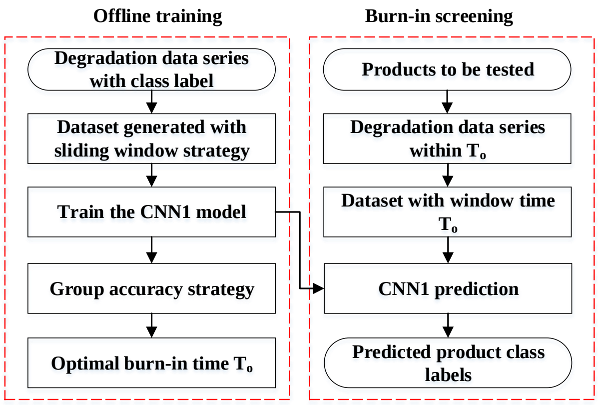

Fig.1. Flowchart of the proposed burn-test method

task of product screening then will be completed. The flowchart of the proposed method is shown in Fig. 1

2. Theories and methods

A. Sliding Window Strategy

The original run-to-failure data set consists of degradation series, each of which has a unique class label representing the true class of the corresponding product, i.e. weak class or normal class. However, due to the principle of burn-in test, it is useless to directly train a model with the original data set. For this reason, a sliding window strategy is applied here. The sliding window strategy is to give a fixed size window and slide the window along a specified direction, which is effective only when the window is filled with degradation data. When the window slides effectively, the data in window and the last measurement time will form a window sample. Particularly, the measurement time will be regarded as the actual burn-in time of the window sample, which is referred to as window time (WT).

B. Convolutional Neural Network

In this paper, CNN1 is used to complete the product screening task. The designed CNN1 consists of one data input layer, four convolution calculation layers, three full connection layers and one classification layer. Besides, the pooling layer is not used, and the same mode of a convolution operation is adopted. Since the same mode is used in convolution layers, and the down-sampling operation is not conducted, the size of the feature maps will remain unchanged after convolution.

C. Group-Accuracy Strategy

Assume that the prediction accuracy of products by CNN1 is positively correlated with the differentiation degree of two-class products, then the prediction accuracy of window samples by CNN1 is also positively correlated with WT. Based on this assumption, a group-accuracy strategy is adopted to obtain the optimal burn-in time. Specifically, group tests are conducted by well-trained CNN1 and the accuracy is obtained for each group. The WT of the group with the highest accuracy and the minimum WT is the optimal burn-in time T_0 we desired. For a group, assuming that the number of window samples is n, WT is t, and denote the predicted label and true label of the *j*th unit respectively by $L_{pj}(t)$ and L_j . Then the group accuracy is defined as

$$G_{acc}(t) = \frac{1}{n}\sum_{j=1}^{n} 1_{\{L_{pj}(t)=L_j\}}(t) \tag{1}$$

Where $1_{\{L_{pj}(t)=L_j\}}(t)$ is the indicator function of the event that predicted label equals to its true label.

And the optimal burn-in duration T_0 is defined as

$$T_0 = \min\{ t_i \mid G_{acc}(t_i) > TH_{acc}, i = 1,2,\cdots,m\} \tag{2}$$

3. Online optimization

The online optimization algorithm involves T_0, well-trained CNN1 and the effective information (EFI). Given a product to be screened, if the results of two adjacent predictions are different, effective information is produced. $EIF(t)$ is thus defined as the sum of the effective information of all products to be screened. When $EIF(t)$ is less than a given threshold, stop the burn-in test and output results, otherwise continue the burn-in test. Denote the class prediction results of products within burn-in time *t* by $RS(t)$, and the prediction of the *i*th product is denoted by $RS_i(t)$ and $RS_i(t-1)$, Then, $EIF(t)$ with n products to be tested is defined as

$$EIF(t) = \frac{1}{n}\sum_{i=1}^{n} 1_{\{RS_i(t)=RS_i(t-1)\}}(t) \tag{3}$$

The online optimization algorithm is proposed. The improved online screening process is shown in Fig. 2.

4. Experiments

Experiments are conducted based on three simulation data sets consisting of laser, LED, and MEMS data. Three representative methods used for comparison are referred in [1-3]. Through analyzing the experimental results, we could obtain the following results.

(i) The online optimization algorithm is successfully applied to dynamically adjust the burn-in time according to the actual degradation information of products.

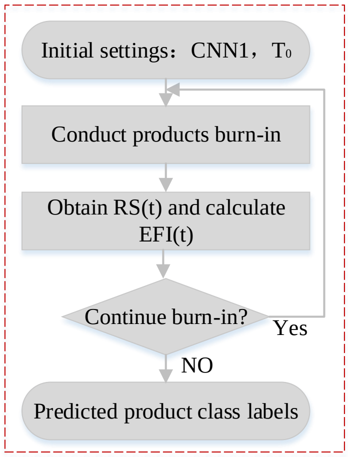

Fig. 2 The improved online screening process

(ii) The influence of noise on cannot be ignored for all burn-in strategies developed off-line, but can be limited or even eliminate by our online optimization algorithm.

(iii) There is a big risk when offline burn-in strategies are used for online testing

5. Conclusion

In this paper, we propose one online burn-in optimization approach based on convolutional neural network. Comparing with the conventional methods, our method has significant advantages. Firstly, the method is entirely driven by degradation data, and hence independent of degradation models, which means that there is no need to have a thorough understanding of the degradation failure mechanism of products, and that various uncertain risks arising from the design of degradation models can be avoided. Secondly, although the optimal burn-in time is obtained in the offline training stage, the actual burn-in time can be adjusted according to the specific situation by the online optimization algorithm, so as to be able to cope with various possible complex degradation situations. Moreover, the proposed method exhibits good robustness and flexibility.

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