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Development of a Normal-State Estimation Model and Accelerated Aging Test of TVS Diode for Fault Diagnosis of Digital Input Modules

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1. Introduction

Ensuring the reliability of programmable logic controller (PLC) boards is crucial for maintaining the safety of nuclear power plants. One of the key components of PLC boards, the transient voltage suppression (TVS) diode, serves to protect circuits from transient overvoltage. However, its performance may degrade due to repeated electrical stress [1].

This study aims to analyze the normal and degraded states of TVS diodes and develop a normal-state estimation model using machine learning. To achieve this, an accelerated aging test was conducted to collect data, and the voltage-current (V-I) characteristics were analyzed. Additionally, a machine learning approach was employed to effectively estimate the normal-state condition of the diode.

2. Methods and Results

To acquire data for fault diagnosis, an experimental setup was constructed. The device under test (DUT) in this study was a TVS diode, subjected to accelerated aging by applying impulse voltage. Normal and degraded state data were collected through these tests. While the manufacturer's datasheet provides an ideal V-I curve, it does not offer information on the range of normal-state variations or the changes in the curve as degradation progresses. In this study, a machine learning model was developed to estimate the normal-state V-I curve based on normal-state data for fault diagnosis.

2.1 Experimental Setup

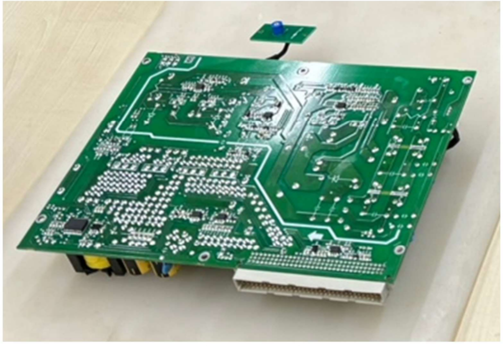
An experimental system was designed to acquire data for diagnosing faults in TVS diodes. The setup consisted of a V-I curve analyzer, a noise immunity tester, a transformer, and a test board (see Fig. 1. The ABI BoardMaster 19 Rack model was used as the V-I curve analyzer, while the NoiseKen INS-400L model was employed as the noise immunity tester. The overall configuration of the test setup is depicted in Fig. 1.

2.2 Experimetal method

TVS diodes function as protective components that suppress transient voltage spikes to prevent damage to electronic components. In this study, accelerated aging tests were performed to induce faults and analyze the degradation mechanisms of TVS diodes. A voltage, adjusted via a transformer, was input into the noise immunity tester, which then applied a 4 kV impulse voltage to the test board for three minutes. After each experiment, the V-I curve of the TVS diode was measured using the V-I curve analyzer, allowing for the acquisition of both normal and degraded state data.

(a) V-I curve analyzer

(b) noise immunity tester & transformer

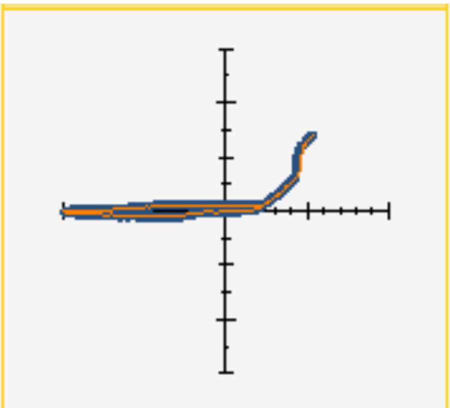


(c) Board

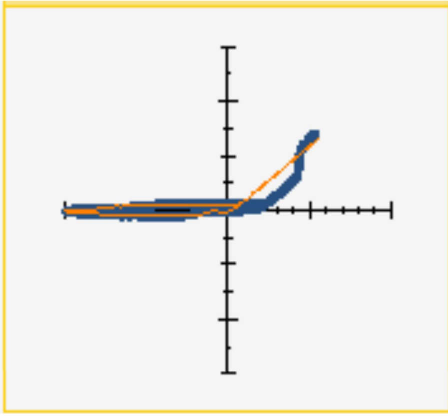
Fig. 1. Experimental setup for board testing..

2.3 Data Generation

During the experiments, a 4 kV impulse voltage was applied to the test board for three minutes through the noise immunity tester. A total of 33 datasets were obtained, comprising five normal-state samples and 27 degraded-state samples. Fig. 2 presents the measured V-I curves of the TVS diodes using the ABI V-I curve analyzer, where Fig. 2(a) illustrates normal-state data, and Fig. 2(b) displays degraded-state data. The variations in the V-I curves indicate the changes in diode characteristics due to degradation. Using this data, a machine learning model was developed to estimate the normal-state V-I curve.



(a) Normal



(b) Fault

Fig. 2. V-I curve analyzer for normal and fault data

2.4 Development of a Normal-State Estimation Model

The TVS diode estimates the steady-state condition based on the V-I curve. To develop a model that estimates the normal-state V-I curve using experimentally obtained normal-state data, a machine learning algorithm was employed. The model was designed with voltage as the input data and current as the output data. Initially, an ANN model was trained, and the results were compared with the test data, as shown in the Figure. 3 below.

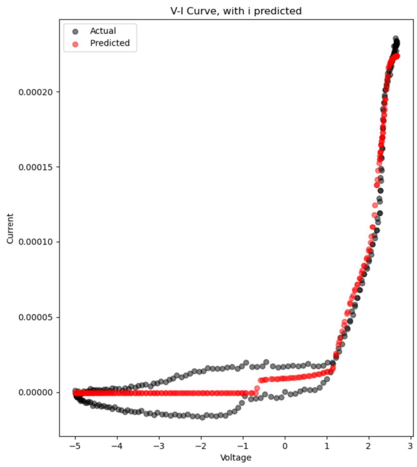


Fig. 3. ANN Model Result with normal

In the region where the voltage is above 1, the model follows the actual values relatively well. However, in other regions, it can be observed that the model predicts intermediate values between the upper and lower bounds. This issue arises because, in the actual data, there are two different currents for the same voltage, leading to predictions of intermediate values. To address this problem, the input data dimensions for specific regions were expanded, and a quadratic polynomial transformation was applied along with changes to the activation function.

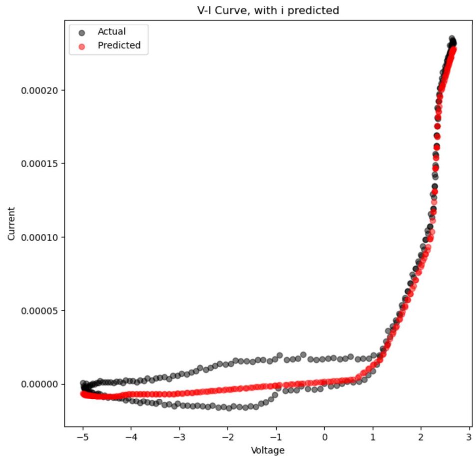


Fig. 4. ANN Model Result with poly

Improvements were observed in the region where the voltage is above 1, but it was still found that the model could not estimate values in other regions. Finally, a clustering technique was applied to implement separate prediction models for each region.

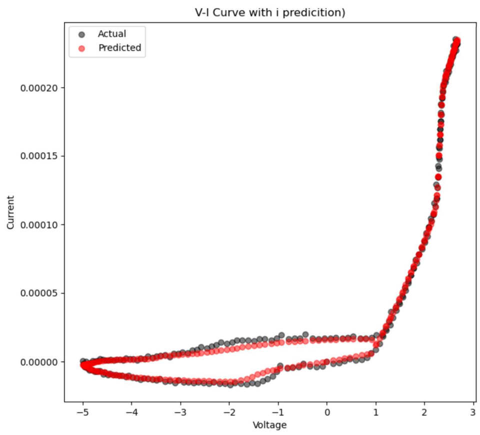


Fig. 5. ANN Model Result with Clustering

3. Conclusions

Data was collected through accelerated aging tests to develop a normal-state estimation model for the TVS diode, a component of the digital input module. The data obtained from the experiments clearly distinguished between the normal-state and fault conditions, but the differences within normal-state data and within fault data were minimal. Future research will focus on developing testing methods to observe gradual changes.

Additionally, a model was developed to estimate the normal-state V-I curve based on the acquired normal-state data. In future studies, the characteristics of normal-state and fault-state variations will be incorporated into the model to build a fault diagnosis framework, and its performance will be validated using actual fault data.

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