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Fault localization of a switched mode power supply based on extended integer-coded dictionary method

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ABSTRACT

Switched mode power supply (SMPS) is widely used in various industrial fields. Due to the complex operational condition, various faults may occur in the SMPS. Localizing the faults efficiently is necessary for the SMPS. Based on the classical integer-coded dictionary (ICD) method, which has been widely used in board-level analog circuits fault localization, this paper presents an extended ICD method to solve the fault localization problem in SMPS. An optimal boundary determination method is adopted in the extended ICD, which can improve the separating ability of each feature. In the paper, faults in SMPS, the available test points as well as the experimental setup are introduced first. Then, the extended ICD method is presented. Finally, the developed method is applied in the SMPS, and the test result shows eight fault states can be isolated only using six features with an accuracy of 92.5%.

1. Introduction

Switched mode power supply (SMPS) is a kind of efficient power supply, which is widely used in many industrial fields. During the operation of the SMPS, many faults may occur due to the electrical, thermal and even radiation stresses.

To localize the potential fault efficiently, a linear separable classification method—integer-coded fault dictionary (ICD) method—was widely used in board-level analog circuits [1–4]. The method uses a matrix to represent the relationship between faults and a series of features, and a specific integer code is assigned to each fault with each feature [5]. Given a combination of determined features, the fault can be quickly localized using such an established integer matrix.

To get integer codes of different faults with a specific feature, a coding rule is required to translate features of different fault states into integers by using a series of boundaries. Two faults coded with the same integer are defined to be in the same ambiguity set. A good selection of boundaries can reduce the possibility of ambiguity set, and improve the fault localization resolution. Traditionally, an arbitrary “ambiguity gap” (0.2 V or 0.7 V) is set to determine the integer intervals [6]. In [7], a clustering method was used to determine the boundaries in ICD. However, this method required to use multiple integers to code each fault, which cannot be used in classical ICD. In [6], the feature distribution is used to determine the boundary instead of the arbitrary “ambiguity gap”. Using this method, the selected boundaries are the same as the upper or lower tail boundaries of some feature distributions. However, it is not necessary to always select the distribution tails as the integer boundaries. If there are two feature distributions far away from each other, selecting a boundary value within the middle of these two distributions is much better than selecting a boundary that is much closer to any one of the distributions.

To solve the coding problem for ICD, an extended ICD method is presented in this paper, which introduces a new practical optimized boundary determination method to code each feature in the classical ICD method. In Section 2, the SMPS, as well as its fault seeding experiment, are introduced first. In Section 3, the developed extended ICD with optimized boundaries is described. The Gaussian mixture model (GMM) is introduced to construct the distributions of features. The genetic algorithm is applied to optimize boundaries. Then, the ICD can be constructed using the boundaries. Finally, the developed method is verified in the SMPS, where six features are used to localize eight fault states. The results show it is able to localize the faults more accurate than the traditional ICD method.

2. Problem description

2.1. Potential faults determination of SMPS

In this paper, a specific SMPS with the flyback topology used for LED road light driving is studied. Fig. 1 shows the functional structure of the LED driver.

Although many components in the SMPS may degrade during the

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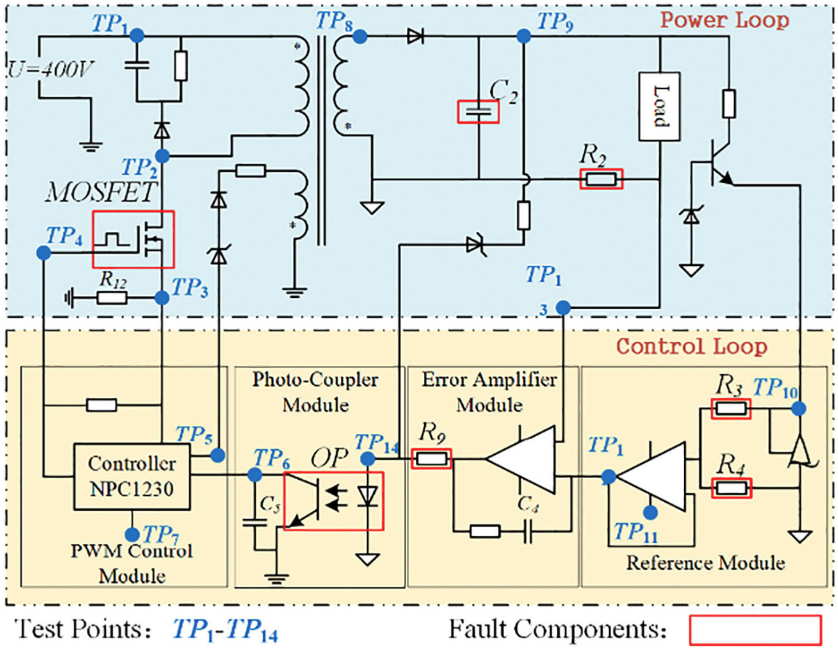

Fig. 1. The functional structure of the LED driver.

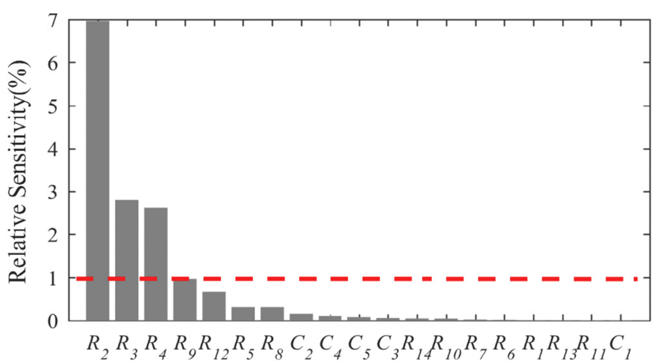

Fig. 2. Sensitivity analysis result.

Table 1
List of potential faults.

Fault code	CMPT.	Fault mode	Fault code	CMPT.	Fault mode
F_0	–	Fault-Free	F_4	R_4	$R+$
F_1	C_2	$C-$	F_5	OP	$CTR-$
F_2	R_2	$R+$	F_6	MOSFET	$R_{DS}-$
F_3	R_3	$R+$	F_7	MOSFET	$R_{DS}+$

operation, most of them cannot influence the SMPS performance severely. In this paper, only components whose degradation can significantly influence the output current are considered. Fig. 2 shows the sensitivity analysis results using PSpice (a commercial electronics design automation software) simulation data, which reveals that R_2, R_3, and R_4 are with highest sensitivities. On the other hand, many studies indicated that the degradation of the power MOSFET, the aluminium electrolytic capacitor, and the photo-coupler often occurred. Thus, these three components and three resistors are defined as fault components, which are listed in Table 1.

2.2. Available features

To limit the number of test points, only input and output points of each structural block are selected (TP_1–TP_{14} in Fig. 1). For each test point, both time and frequency domains features, such as the mean value, the peak-to-peak value, and the frequency, are extracted. Then, a fault sensitive index for each feature is defined to indicate the importance of each feature, which is shown as follows:

$$Index_j = \sum_{i=1}^{m} \left| \frac{\mu(t_j \mid F_i) - \mu(t_j \mid F_0)}{\sigma(t_j \mid F_i) - \sigma(t_j \mid F_0)} \right| \tag{1}$$

where $\mu()$ and $\sigma()$ denote the mean value and the standard deviation of a given data set. Six features with highest scores are selected, which are noted as t_1 to t_6, respectively. The feature notations, as well as the corresponding physical meanings and test points, are also listed in Table 2, where V refers to the voltage of the specific test point.

2.3. Fault seeding experiment

To collect features from the SMPS, the fault seeding experiment should be conducted. Fig. 3 shows the experimental setup.

During the experiment, fault components were seeded in the SMPS (part B) manually, and the oscilloscope Keysight DSO5012A (part D) can capture waveforms of all test points. The PC (part A) controls the DAQ control board (part C) to connect the channels with certain test points. In the experiment, the tolerances of fault-free components should also be considered. For each fault, 10 observations of features

Table 2
List of selected features.

Code	Physical meaning	Code	Physical meaning
t_1	Max. of V_{TP4}	t_4	Mean of V_{TP9}
t_2	Mean of V_{TP5}	t_5	Max. of V_{TP8}
t_3	Mean of V_{TP10}	t_6	Peak-peak of V_{TP9}