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Monitoring chip fatigue in an IGBT module based on grey relational analysis☆

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ABSTRACT

Chip fatigue inside an insulated gate bipolar transistor (IGBT) module is a kind of incipient defect. It can be considered as an indication of the impending failure, and is utmost important for the safe operation of IGBT modules. Therefore, monitoring the chip fatigue is one of crucial measures to enhance the operating reliability of IGBT modules. This paper presents a prognostic approach for the chip fatigue based on grey relational analysis (GRA), which uses dynamic change of the gate voltage as precursor parameter. This dynamic change is caused by aging of the intrinsic parasitic elements involved in gate drive circuit, which reflect the advent of chip fatigue. Grey relational grade is employed in this proposed prognostic approach to quantify the extent of those dynamic changes by little data, and find out potential chip fatigue. Then the operator would have a chance to schedule the maintenance and replace defective IGBT modules timely to avoid wear out. So it can be seen as a prefault diagnostic method. Finally, a confirmatory experiment is also carried out, and the correctness of the proposed approach is verified.

1. Introduction

Nowadays, the IGBT becomes one of the key power electronic devices, and is widely used in many safety-critical fields such as aerospace, traction, electric vehicles and renewable energy, where stringent reliabilities are more preferable than other usual industry applications [1–3]. By combining both merits of power MOSFETs and power BJTs, IGBTs can conduct high current at high voltage and high switching frequency, and their ratings have reached as high as 6.5 kV/0.6 kA or 1.7 kV/3.5 kA [4]. Moreover, the reliability of IGBTs has also been significantly developed in recent years, the failure rate dropped from 1000 FITs in 1995 to 20 FITs in 2000, and to only a few FITs currently [5], where 1 FIT $= 1 \times 10^{-9}$ failures per device-hour. However, in safety-critical fields such as traction and wind power generation, IGBTs operate in uncertain and harsh environments, may undergo huge electrical and thermal stresses. For example, an IGBT module used in electrical traction driver for an urban tram may experience 10^6–10^8 power cycles, with junction temperature swings up to 80 °C, during its lifetime [5]. Similarly, in wind power generation applications, the widely varying and intermittent nature of the wind speed and low converter modulation frequencies also critically affect the reliability of IGBTs due to the thermal cycling [6]. Therefore, the converter has the dominating effect on the system reliability [7]. In general, power semiconductor devices contribute more than 20% failures of converters, and IGBTs are the most used devices. So detecting reliability degradation of IGBTs becomes an important issue and gains increasing attention from industry [8]. Many researches on detecting reliability degradation of IGBTs were reported over the last decade, and most of them were based on external indication of aging or physical of failure. In [9,10], the collector–emitter saturation voltage $V_{CE(sat)}$ was utilized as an early symptom and warning sign of IGBT module degradation. In [11], the high-order oscillatory responses present in the voltages and currents of the system were used to assess the aging status of the power electronic circuit. In [12,13], the changes of an inverter output harmonics and the case temperature of the IGBT module were used to identify the increase of internal thermal resistance because of solder fatigue. Moreover, the physical of failure for IGBTs was adopted to calculate life consumption of IGBTs [14,15]. Unfortunately, the relevant research on detecting reliability degradation of IGBTs is still in its embryonic state [12].

The major limiting factor in evaluating reliability of IGBTs is that most of physical wearout mechanisms give little external indications of impending failure [16]; only existing several precursor parameters [17]. Furthermore, most of them are difficult to be obtained, for example, the on-state collector–emitter saturation voltage $V_{CE(sat)}$ as mentioned in [9,10]. First, it is difficult to measure a few millivolts change in $V_{CE(sat)}$ in the on-state, which is highly susceptible to switching noise, and second the $V_{CE(sat)}$ changes with the junction temperature T_j, while sensing the junction temperature during converter operation is almost impossible [18]. To overcome this limit, the theoretical

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background of oscillations in the gate voltage caused by incipient defect, such as chip fatigue, was detailed in [19]. Those measurable oscillations, i.e. dynamic changes of the gate voltage are feasible used as a potential precursor parameter for monitoring chip fatigue. However, sensing the gate voltage during the converter running is easily influenced by many uncertain factors and limited by the fast switching transient. In other words, only little data is acquirable. It means general algorithm, like Euclidean distance, is not ideal to distinguish fine distinctions in the gate voltage. For this, the grey relational analysis theory is introduced in this paper because it is just suitable to deal with the uncertainty in little data, incomplete information. The method proposed in this paper is unlike the post-fault detection [20]. By monitoring chip failure operators are able to assess the current health level of an IGBT module and find out the unhealthy IGBT module in a pre-fault condition, then replace it timely to avoid burnout and subsequent collateral damage to the rest of the converter. In addition, monitoring the incipient defect would allow scheduled maintenance and result in considerable cost saving comparing to emergency repair.

The rest of this paper is organized as follows. First, the theory of GRA is explained in depth. Second, transient characteristics of the gate voltage as affected by chip failure are discussed, and then a prognostic approach based on GRA is proposed. Finally, the feasibility of this approach is verified via experimental data.

2. Grey relational anslysis

2.1. Theory of GRA

The GRA is one of essential contents of the grey system theory (GST) formulated by Deng Julong in 1982 [21]. The concept of the grey system contains systems in which part of information is known and part of information is unknown. The word "grey" here means poor, incomplete, uncertain, etc. The GRA uses a specific concept of information named difference information space which can be visually interpreted as soaking plane resulted from a drop of ink on a white paper [22]. It combines the distance space with point-set topology. It is well known that the distance space is based on numerical measure, but limited to two points devoid of wholeness and reference, and the point-set topology is characterized by neighborhood and wholeness, but devoid of numerical measure. In order to overcome those shortcomings, the difference information space is developed and used to set up the contrasting mechanism of the GRA in [23].

Let the original reference sequence and comparability sequences be represented as $x_0^{(0)}(k)$ and $x_i^{(0)}(k)$, and their absolute difference at point k be denoted by $\Delta_{0i}(k)$, where $i=1,2,\ldots,m; k=1,2,\ldots,n$, respectively. Then the difference information space LY_{gr} can be written as

$$LY_{gr} = \left\{ \Delta_{0i}(k) \middle| \forall \Delta_{0i}(k) \in \left[\min_i \min_k \Delta_{0i}(k), \max_i \max_k \Delta_{0i}(k) \right] \right\} \quad (1)$$

where

$$\Delta_{0i}(k) = \left| x_0^{(0)}(k) - x_i^{(0)}(k) \right|. \quad (2)$$

Overall, the GRA does not attempt to find the best solution, but does provide an appropriate solution for real world problems. In recent years, it gains increasing attention and is widely used in many fields [24,25].

2.2. Grey relational generation

In the grey relational analysis, data preprocessing is normally required when the sequence scatter range is too large as background noises is always there. This data preprocessing, also known as "grey theory relational generation", is a process of transferring the original sequence to a comparable sequence. There are various methodologies for data preprocessing, in which a linear data preprocessing method is commonly used.

$$x_i^*(k) = \frac{x_i^{(0)}(k) - \min x_i^{(0)}(k)}{\max x_i^{(0)}(k) - \min x_i^{(0)}(k)} \quad (3)$$

where $x_i^*(k)$ is the value after the grey relational generation, $\min x_i^{(0)}(k)$ is the smallest value of $x_i^{(0)}(k)$, and $\max x_i^{(0)}(k)$ is the largest value of $x_i^{(0)}(k)$.

2.3. Grey relational coefficient

After data preprocessing, the grey relational coefficient at point k can be calculated using the following formula

$$\gamma\left(x_0^*(k), x_i^*(k)\right) = \frac{\Delta_{\min} + \xi \Delta_{\max}}{\Delta_{0i}(k) + \xi \Delta_{\max}} \\ 0 < \gamma\left(x_0^*(k), x_i^*(k)\right) \le 1 \quad (4)$$

where $\Delta_{\min} = \min_i \min_k \Delta_{0i}(k)$, $\Delta_{\max} = \max_i \max_k \Delta_{0i}(k)$, and $\xi \in [0,1]$, is distinguishing coefficient.

Then the grey relational grade is obtained

$$\gamma(x_0, x_i) = \frac{1}{n} \sum_{k=1}^{n} \gamma\left(x_0^*(k), x_i^*(k)\right). \quad (5)$$

Here, the grey relational grade $\gamma(x_0, x_i)$ represents a numerical measurement of correlation between the reference sequence and the comparability sequence. The more coincidence those two sequences are, the closer that the value of grey relational grade is to 1.

3. Chip fatigue monitoring method

3.1. Precursor parameter and verification

Here the dynamic change of the gate voltage in the turn on process is used as precursor parameter to monitor chip fatigue in an IGBT Module. However, the gate voltage V_{GE} is closely coupled with collector–emitter voltage V_{CE} though the collector-gate capacitance C_{GC} etc. as investigated in [19]. Thus, the direct use of the gate voltage may lead to a mistake because V_{CE} differs in different applications. Fortunately, there is a special time interval in the turn on process i.e. the interval of $t_0 - t_1$ as shown in Fig. 1, during which all the intrinsic parameters of the gate

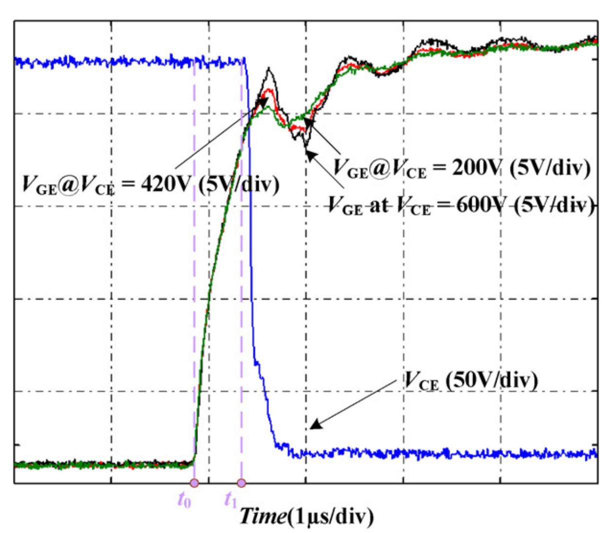

Fig. 1. Turn-on waveforms of the gate voltage according to different collector–emitter voltages.