CRANFIELD UNIVERSITY

Yuan’an Xie

Prognostics for Electronics Components of Avionics – NASA IGBT Accelerated Ageing Case Study

School of Engineering

MSc by Research

MSc Thesis

Academic Year: 2012 - 2013

Supervisor: Dr. Tarapong Sreenuch & Prof. Antonois Tsourdos

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ABSTRACT

Insulate gate bipolar transistors (IGBTs) are widely used in electric vehicles, railway locomotive and new generation aircrafts, due to the IGBTs have advantages in small conduction resistance and small drive current. Hence, the reliability of IGBTs directly affect the reliability and performance of these vehicle systems. In recent years, a series of research works about IGBT reliability, failure mode and ageing analysis have been carried out widely, and a suitable prognostics method for IGBT and an efficient algorithm for predicting the IGBT Remaining Useful Life (RUL) become increasingly important.

In recent years, despite the research works on IGBT reliability, failure mode and effect analysis are carried out widely, the prognostics and prediction of the IGBT remaining useful life are still the bottleneck in the research work to develop IGBT health management system.

In this thesis, a framework and algorithm of IGBT prognostics and RUL prediction were developed. The research was based on the IGBT accelerated ageing experiments. The IGBT ageing data were processed and analysed, and the mechanism of the IGBT degeneration was studied. Additionally, the IGBT degradation models were built to simulate the IGBT degeneration process which were utilised to develop the prognostics algorithm for predicting the IGBT RUL.

Gamma distribution model, Exponential distribution model, Poisson distribution model and the combining distribution model were established, and Monte Carlo simulation was utilised in the algorithm to compute the IGBT remaining useful life. The collector emitter voltage (V_{CE}) was used as precursor parameter in prognosis to predict the RUL. Seven IGBTs were experimented in this prognostics research.

The RUL prediction results were analysed and compared, and the prognostics algorithm was developed and summarised. The accuracy of the RUL prediction was presented, and the root mean square error was utilised to analyse and compare the efficiency and applicability of different models. The study of the

IGBT prognostics and algorithm development were summarised and demonstrated.

ACKNOWLEDGEMENTS

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AAS	Accelerated Ageing System
BiFET	Bipolar Field Effect Transistor
CCD	Charge Coupled Device
CH	Calinski-Harabasz
COMAC	Commercial Aircraft Corporation of China, Ltd.
COMFET	Conductivity-Modulated Field Effect Transistor
CU	Cranfield University
GEMFET	Gain-Enhanced Metal Oxide Semiconductor Field Effect Transistor
I_{CE}	Collector Emitter Current
IGBT	Insulate Gate Bipolar Transistor
IGR	Insulated Gate Rectifier
IVHM	Integrated Vehicle Health Management
MOSFET	Metal Oxide Semiconductor Field Effect Transistor
NASA	National Aeronautics and Space Administration
PC	Personal Computer
RMSE	Root Mean Square Error
RUL	Remaining Useful Life
RUL_P	Predicted Remaining Useful Life
RUL_R	Real Remaining Useful Life
RVM	Relevance Vector Machine
T_i	Duration Time of the degeneration phase
V_{CE}	Collector Emitter Voltage
V_{GE}	Gate-Emitter Voltage
VI	Virtual Instrument
VTB	Virtual Test Bed

1 Introduction

1.1 Research Project Overview

In this thesis, the study is based on the NASA IGBT accelerated ageing experiments and ageing data sets. IGBT accelerated ageing experiments and ageing data are studied and analysed in this thesis. According to the IGBT failure mechanism and degradation characterization, the IGBT degeneration models are built. Monte Carlo simulation method and the precursor parameter, collector emitter voltage (V_{CE}), are integrated to develop the prognostics algorithm on predicting the IGBT remaining useful life (RUL), and then the RUL prediction results are analysed, and the advantage of different models in predicting the IGBT RUL is compared and analysed. Finally, the conclusion is summarised.

1.2 Motivation

1.2.1 IGBT Accelerated Ageing Experiment

Nowadays in order to provide warning and predict failures to avoid calamitous failure of products and systems, there has been an increasing tendency in monitoring the ongoing "health" of them [1]. The IGBT modules play an increasing significant role in on-wing for avionics system, such as communication system in autonomous working, radar system and navigation system and so on. The failures of IGBT components can degrade the efficiency of the systems or result in system failures [2].

In order to be able to predict its failure, a process that can cause an IGBT module to fail must be devised. In general, IGBT modules have several thousand hours' lifetime expectancy [3], but in order to analyse failures from several of them, the lifetime of the modules needs to be reduced. Therefore the process that causes it to fail must still operate the module within its specifications, but in a greatly reduced time frame.

Ergo IGBT accelerated ageing experiments system was developed to investigate the degradation of IGBT and the adoption of precursors for diagnosis and prognosis.

IGBT Accelerated Ageing System is to design and implement a system capable of performing robust experiments on gate controlled power transistors to induce and analyse prognostics indicators [4]. The main goal for the development of experiment system was to identify precursor parameters for device failure, Precursor parameters are parameters of the device that change with time wherein the change can be mapped to degradation in the device. Once the precursor parameters are identified, suitable diagnostics and prognostics algorithms can be implemented using these parameters to provide early warning of failure and predict remaining useful life [5].

Hence, a comprehensive approach to the development of a prognostics framework for IGBTs is required, there is a necessity to develop methods to predict the remaining useful life (RUL) of IGBTs to prevent system stoppage and costly failures. In this study, a framework and study of IGBT prognostics and RUL prediction were developed.

1.2.2 Market Condition and Industry Requirements

Prognostics is very commonly used in high technology sectors, for example the automotive and aerospace industries, for ensuring safety and customer satisfaction. Most modern vehicles monitor their systems to ensure correct operation [6]. If a fault is detected or predicted the user of the vehicle is usually notified before the fault has had a detrimental effect on the vehicle. Modern vehicles also monitor their usage and change their service intervals accordingly.

Insulate gate bipolar transistors (IGBTs) are widely used in electric vehicles, railway locomotive and new generation aircrafts, due to the IGBTs have advantages in small conduction resistance and small drive current [7]. Hence, the reliability of IGBTs directly affects the reliability and performance of these vehicle systems. In recent years, a series of research works about IGBT reliability, failure mode and ageing analysis have been carried out widely, and a suitable prognostics method for IGBT and an efficient algorithm for predicting the IGBT RUL become increasingly important.

In recent years, although the research works on IGBT reliability, failure mode and effect analysis are carried out widely, the prognostics and prediction of the IGBTs remaining useful life (RUL) are still the bottleneck in the research work to develop IGBT health management system.

As electronic components have an increasing application in new generation aircrafts and vehicles, and the amount of electronic failure will also become significant. Fault diagnosis and prognostics, estimation of remaining useful life and health management have a vital role to avoid hazard failure and improve aircraft reliability, reduce maintenance cost and increase performance [8].

Hence, this study is research on IGBT to develop algorithm to estimate remaining useful life of components, and it is considered to contribute to the prognostics technology development in Integrated Vehicle Health Management (IVHM) field and advance the electronic components prognosis.

1.3 Background

1.3.1 Prognostics Approach

Prognostics is the approach of predicting the future situation or health of products or systems by estimating the extent of degradation or deviation from their expected normal working conditions, and by using appropriate models and algorithms to predict the behaviour to failure thresholds [9].

Prognostics is used to predict the remaining useful life (RUL), and this is one of the most significant goals for the prognostics system. It is also the aim of this thesis to develop the algorithm of prognostics. Presently, the most prevailing prognostics approaches include data-driven methods and model-based methods [10]. Data driven prognostics methods utilise precursor data recorded by sensor, which are used to monitor the conditions of the research object, to predict the future operating condition of the system. Relationship between sensor data and mechanisms of degradation and fault will be analysed and utilised to forecast the healthy condition. Model based methods use modelling approach to predict the remaining useful life of the system.

There are several approaches that have been developed for electronic prognostics. A few examples of these prognostics approaches will be described. The current state of research on prognostics of IGBTs will be discussed in detail. The issues unaddressed in previous IGBT prognostics studies will form the basis for the motivation of the current study.

Saha et al. [11] used a system model approach to estimate the remaining useful life of lithium ion batteries. The battery was represented by a lumped parameter model. The parameters of the model were calculated using relevance vector machine (RVM) regression on experimental data. An extended Kalman filter and particle filter algorithms were used to determine the battery RUL.

Goodman et al. [12] described the use of prognostics cells to predict failure in integrated circuits. The prognostics cell is developed to fail prior to the circuit on the same chip for all realistic operating conditions. Prognostics monitors in the test cell see the exact environment that the actual circuit sees, but at an accelerated rate, thereby providing failure prediction.

Kumar et al. [13] used the data-driven approach to detect anomalies of notebook computers by monitoring performance parameters and comparing them against the historical data using Mahalanobis distance.

A physics-based prognostics approach was used by Cristaldi [14] in the development of a diagnostic system based on a virtual system. Using a Virtual Test Bed (VTB), system faults found in a real world system were simulated along with a normally operating real world system.

For the development of a fault diagnostic system for a brake-by-wire system, Murphey [15] used a similar fuzzy system approach. Six failure modes of the system were identified and three measurement points chosen. The input signals were processed on a segment-by-segment basis, by a feature extraction process, and by fault detection.

1.3.2 IGBT Prognostics

IGBT has been reported to fail suffering extreme electrical and thermal stresses in variable speed drives, and are considered as reliability problems in wind turbines [16], inverters in hybrid electric vehicles and railway traction motors [17]. There is a need to develop methods to detect anomalous behaviour and predict the remaining useful life (RUL) of IGBT to prevent system downtime and costly failures.

IGBT prognostics is a relatively new field with limited studies reported in literature. The majority of the studies are on development of diagnostic techniques to detect anomalies in applications such as automotive, motor drive [7] and railway traction systems.

1.4 Dissertation Scope and Outline

In this thesis, a framework and study of IGBT prognostics and RUL prediction was developed. The IGBT ageing data were processed and analysed, and the mechanism of the IGBT degeneration was studied. Additionally, the IGBT degradation models were built to simulate the IGBT degeneration process and utilised to develop the prognostics algorithm for predicting the IGBT RUL. The RUL prediction results were analysed and compared, and the prognostics algorithm was developed and summarised. The accuracy of the RUL prediction was presented, and the root mean square error was utilised to analyse and compare the efficiency and applicability of different models.

The research scope and research contents of this study is presented in chapter 1, additionally the motivation of researching IGBT ageing experiment and prognostics is introduced. The background of the prognostics is described.

In chapter 2, the research contributions and research aim, objectives are presented. Chapter 3 is the literature review, and the IGBT mechanism and characterization, failure mode and degeneration are studied. IGBT accelerated ageing experiments are also investigated. The current research works on IGBT are summarised.

Chapter 4 involves IGBT accelerated ageing experiments, IGBT ageing data and degradation modelling. The ageing data are processed and the degradation profiles of IGBT are analysed. Maximum likelihood method is utilised to computing the model parameters. In chapter 5, Monte Carlo simulation method and IGBT degradation models are used to predict the RUL, and the algorithm of IGBT prognostics is developed.

The RUL prediction results are analysed in chapter 6 and the errors and root mean square errors are analysed to compare the efficiency of different models in predicting the RUL. In chapter 7, the conclusion is summarised and the future works are discussed.

2 Research Aim & Objectives and Contributions

2.1 Research Aim & Objectives

The research aims to develop a degradation model and approach for predicting remaining useful life of power electronics components (e.g. IGBTs) critical to avionics systems, all of which are required for an aircraft system level health management.

The objectives are:

- To study failure mechanisms and degradation profiles of a power electronics component (e.g. IGBT).
- To apply stochastic processes in modelling degradation (from experimental data) of a power electronics component.
- To develop an estimation algorithm to determine degradation level of a power electronics component based on sensor measurements.
- To develop a predictive algorithm for, based on current degradation level, estimating the remaining useful life of a power electronics component.

2.2 Contributions

The main contribution of this study is the development and implementation of a prognostics framework for IGBTs, and a prognostics algorithm with Monte Carlo simulation and with the collector emitter voltage as a precursor parameter is developed.

Specifically, the IGBT prognostics approach in this thesis developed by the author, which uses probability distributions to model the IGBT degeneration phases and Monte Carlo simulation to predict IGBT remaining useful life, is novel in the field of the IGBTs prognostics and health management. In contrast with the conventional Hidden Markov approach which computes for each time step of the whole ageing process, this new prognostics approach which computes according to the duration time based on the degeneration phase is more suitable for real-time prognostics and implemented in a low computational power devices, like embedded hardware.

Additionally, a combining model which combines one stochastic model based on the duration time of the IGBT degeneration phase and one stochastic model based on the ending time of the IGBT degeneration phase is developed to implement in RUL prediction. Especially, this combining model performs better than other conventional models in the prognostics of IGBT No.1 and No.7

Furthermore, seven IGBT in ageing experiments were implemented in prognostics, and the remaining useful life of the IGBTs were predicted. The results of the prediction were analysed. The efficiency of different stochastic models on predicting the IGBTs were compared.

Finally, in this study, a prognostics approach based on the Monte Carlo simulation and stochastic models is developed, compared with other prognostics approaches, less precursor parameters are required and the prediction efficiency is as high as some other complex prognostics approaches, this prognostics approach is, probably, to be easier to be used in application.

2.3 Publication

Parts of this thesis have been published by the authors:

•T. Sreenuch , A. Alghassi and Y. Xie (2013). *Probabilistic Monte-Carlo Method for Modelling and Prediction of Electronics Component Life*. Submitted to: International Journal of Advanced Computer Science and Applications.

•Y. Xie (2014). *Prognosis of Power Electronics Components Applies in Aircraft Maintenance*. Submitted to: Science & Technology Information (China).

3 Literature Review

3.1 IGBTs

The insulated-gate bipolar transistor or IGBT is widely applied as its character of electronic switch, is a three-terminal power semiconductor device [18]. It is mainly used to fast switch and combine electrical circuit in high efficiency in newer devices [19]. The insulated-gate bipolar transistor is also called the conductivity-modulated field effect transistor (COMFET), insulated gate rectifier (IGR), bipolar field effect transistor (BiFET), gain-enhanced metal oxide semiconductor field effect transistor (GEMFET) and injector field effect transistor [20].

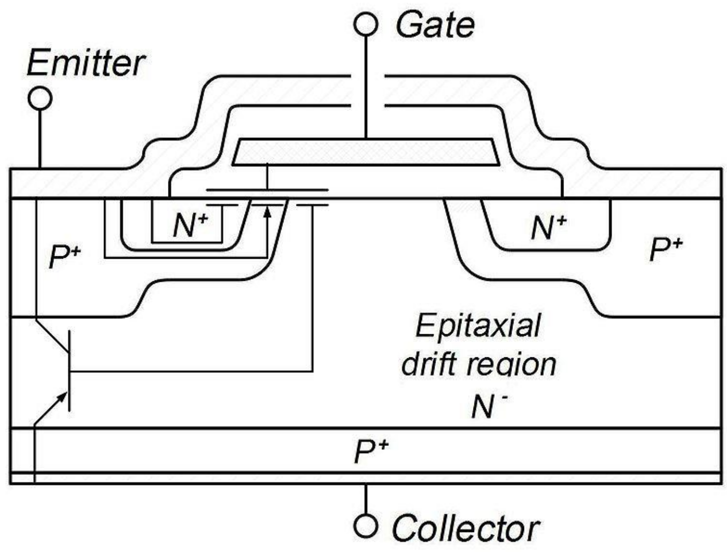

Figure 3-1 IGBT [2]

An IGBT unit is similar to an n-channel vertical construction power Metal Oxide Semiconductor Field Effect Transistor (MOSFET), while the former is constructed by the p+ collector layer, the MOSFET with n+ drain. Which is the same construction as a vertical PNP bipolar junction transistor [21] as seen in Figure 3-1. The main characteristic of the IGBT configuration is that the bottom of the device is formed by the collector (drain) while the emitter (source) region is the same as a traditional MOSFET. Figure 3-1 indicates the schematic construction of the n-channel IGBT. The additional p+ layer in the IGBT is injected into the drift region which acts as a source of holes during operation. These injected holes enable switch-off rapidly when they recombine with the excess electrons remained in the body of the IGBT after turned-off [22].

IGBT has been reported to fail suffering extreme electrical and thermal stresses in variable speed drives, and are considered as reliability problems in wind turbines [16], inverters in hybrid electric vehicles and railway traction motors [17]. There is a need to develop methods to detect anomalous behaviour and predict the remaining useful life (RUL) of IGBT to prevent system downtime and costly failures.

3.2 IGBT Failures and Degradation Process

The most common failure modes for IGBT modules used in power converters of the power and voltage associated with this thesis, as described in Chapter 4, is bond wire lift off and stress cracks in the solder that joins the various parts of the IGBT modules [23].

Degradation means the performance of products is reducing, the reliability is decreasing and their life is shortening. The covariates of the products age or deteriorate are the main reason of degradation. In other words, reliability declines and products failure caused by degradation usually [24]. Many failure mechanisms can be traced to an underlying degradation process, and degradation models represent the underlying prognostics.

Degradation could be classified into two types: forced degradation and natural degradation. Forced degradation is external to systems, where its loading according to the increased demand increases gradually, when the threshold is reached exceed which the systems cannot carry the load safely. However, natural degradation is based on age or is time-dependent. The term ageing refers to a gradual degradation that occurs in systems as an internal process, thus it makes the systems fail [25].

A major reason for the failure of IGBTs is bond wire lift-off [26], which results from the thermal cycles the device is subjected to in operation. As the temperature of the device cycles, the difference in the thermal expansion coefficients of the two materials causes stress to build up in the bonding interface between the wire and the silicon. The bond wires then become disconnected and the device fails into an open circuit. If the device has multiple bond wires, the wires closest to the centre of the chip experience the stress, as this is where the junction temperature is at a maximum. When they fail, the remaining bond wires have to carry the full current of the device and as a result they will subsequently also fail. This phenomenon is not only confined to the high current carrying wires; Ciappa has shown that gate bond wires can also fail as a result of stress induced by thermal cycling [27]. He developed a model to predict the failure of IGBTs using experimental data for bond wire lift-off failures. However, he notes that this model is for aluminium bond wires and does not take into consideration countermeasures to bond wire lift-off that have been developed and are now increasingly being used on new IGBT modules, e.g. strain buffers and bond wire coatings.

IGBTs can also fail through partial discharge [28]. This is a particular problem for high voltage IGBTs (over 1.5kV). Partial discharge has been found to occur in the silicon gel on the metallisation edges and interfaces of the device and is the result of imperfect etching of the silicon during manufacture. Fabian has taken this research further using Charge Coupled Device (CCD) technology to record the small light intensities that are emitted by electro-luminescence effects as well as the light caused by actual partial discharge [29]. He found that the main causes for insulation ageing are water trees, partial discharge and electrical trees. Water trees are formed when the silicon gel comes into contact with an aqueous electrolyte. Ions penetrate the insulation and a diffuse structure of micro voids are formed. Electrical trees are similar but are a result of the breakdown of the insulation by an electric field. They propagate into the insulation in a tree-like shape with a branch-like spiky structure. Both Mitic [30] and Fabian [31] concur that these insulation breakdowns take place at high electric field strengths and therefore partial discharge does not have to be considered for IGBTs operating below 1kV.

3.3 IGBT Ageing Experiment and Prognostics

Nowadays, in order to provide warning and predict failures to avoid calamitous failure of products and systems, there has been an increasing tendency in monitoring the ongoing "health" of these products [1]. The IGBT modules play an increasingly significant role in on-wing for avionics system, such as communication system in autonomous working, radar system and navigation system and so on. The failures of IGBT components can degrade the efficiency of the systems or result in system failures [2].

In order to be able to predict its failure, a process that can cause an IGBT module to fail must be devised. In general, IGBT modules have several thousand hours' lifetime expectancy [3], but in order to analyse failures from several of them, the lifetime of the modules needs to be reduced. Therefore the process that causes it to fail must still operate the module within its specifications, but in a greatly reduced time frame.

Ergo, IGBT accelerated ageing experiments system was developed to investigate the degradation of IGBT and the adoption of precursors for diagnosis and prognosis.

IGBT Accelerated Ageing System (AAS) is to design and implement a system capable of performing robust experiments on gate controlled power transistors to induce and analyse prognostics indicators [4]. The main goal for the development of the experiments system was to identify precursor parameters for device failure. Precursor parameters are parameters of the device that change with time wherein the change can be mapped to degradation in the device. Once the precursor parameters are identified, suitable diagnostic and prognostics algorithms can be implemented using these parameters to provide early warning of failure and predict remaining useful life [5].

Implementation of the accelerated ageing system involved developing the hardware and software to perform power cycling of power semiconductor devices. The experimental test bed for this project was developed by Sonnenfeld et al [13].

The device parameters that are monitored include the gate-emitter voltage (V_{GE}), collector-emitter current (I_{CE}), collector-emitter voltage (V_{CE}) and case and package temperatures. The data are stored in a structure array that is compatible with Matlab. This allows for easy interface with diagnostics and prognostics algorithms that are developed using Matlab. The accelerated ageing system is autonomous. The user only initiates the test sequence. When the device under test fails, the system shutdown is initiated automatically [4].

IGBT prognostics is a relatively new field with limited studies reported in literatures. The majority of the studies are on development of diagnostics techniques to detect anomalies in applications such as automotive, motor drive, avionics [7] and railway traction systems.

3.4 Prognostics Approach and RUL Prediction

Prognostics is used to predict the remaining useful life (RUL), and this is one of the most significant goals for the prognostics system. It is also the aim to develop the algorithm of prognostics. Presently, the most prevailing prognostics approaches include data-driven methods and model-based methods [10]. Data driven prognostics methods utilise precursor data recorded by sensors, which are used to monitor the condition of the research object, to predict the future operating condition of the system. Relationship between sensor data and mechanism of degradation and fault will be analysed and utilised to forecast the health condition. Model based methods use modelling approach to predict the remaining useful life of the system.

There are several approaches that have been developed for electronic prognostics. A few examples of these prognostics approaches will be described. The current state of research on prognostics of IGBTs will be discussed in detail. The issues unaddressed in previous IGBT prognostics studies will form the basis for the motivation of the current study.

Saha et al. [11] used a system model approach to estimate the remaining useful life of lithium ion batteries. The battery was represented by a lumped parameter model. The parameters of the model were calculated using relevance vector machine (RVM) regression on experimental data. An extended Kalman filter and particle filter algorithms were used to determine the battery RUL.

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For the development of a fault diagnostic system for a brake-by-wire system, Murphey [15] used a similar fuzzy system approach. Six failure modes of the system were identified and three measurement points chosen. The input signals were processed on a segment-by-segment basis, by a feature extraction process, and by fault detection.

3.5 Summary

From this review, although several approaches have been investigated for specific applications, it could be concluded that an efficient IGBT prognostics approach based on the IGBT degradation mechanism and features for predicting remaining useful life with finite precursor parameters is required to be developed.

4 IGBT Degradation Modelling

4.1 IGBT Ageing Data Collection and Processing

4.1.1 IGBT Ageing Experiments System

The main goal of the IGBT accelerated ageing experiments system is designed to study the ageing characters of the IGBT and develops the algorithm of prognostics for prediction of the remaining useful life. The IGBT degradation data set is acquired from the ageing process system, which was provided by the Ames laboratory of NASA [32], and the data set is utilised to develop and design prognostics algorithm for semiconductor components such as IGBTs having an increasing application in modern multiple vehicle systems.

IGBT accelerated ageing experiments belong to the project in NASA to investigate the degradation characterizations of electronic components [32], as electronic components have an increasing utilisation in new generation aircrafts and vehicles, and the amount of electronic failure will also become significant. Fault diagnosis and prognostics, estimation of remaining useful life and health management have a vital role to avoid hazard failure and improve aircraft reliability, reduce maintenance cost and increase performance. The degradation mechanism of electronic components are generally different from mechanical systems [33], ergo IGBT accelerated ageing experiments system was developed to investigate the degradation of IGBT and the adoption of precursors for diagnosis and prognosis. In additional, algorithm of prognosis for IGBT which used to predict the remaining useful life will be studied and developed via these experiments and research [32].

IGBT accelerated ageing experiments provide prognostics data set which are utilised to develop and compare various algorithms for IGBT prognosis and RUL estimation. Several variables are recorded including experimental environment condition parameters and IGBT degradation characterization parameters [34], which are the main research object in this thesis. Prognostics algorithm development now is the main bottlenecks in IVHM domain [32]. Hence, IGBT accelerated ageing experiments are the significant input to the prognostics algorithm development, which is used to estimate remaining useful life of components. It is also considered to contribute to the prognostics technologies development in the broader field and advance the electronic components prognosis.

IGBT accelerated ageing experiments are based on the ageing platform which induces the degradation and electronic faults into the test system. Prevalently, four kinds of accelerated ageing methods are widely used in accelerated ageing experiments, which are thermal cycling, hot carrier injection, electrical over-stress and time-dependant dielectric breakdown stimulus [33]. The IGBT functional failure such as die solder degradation and wire lift are brought by the thermal cycling accelerated ageing approach. Hot carrier injection could accelerate electrons and holes pass into gate oxide, which could result in the increase of IGBT threshold voltage. IGBT condition mutation and lighting could be caused by the electrical overstress due to the excessive voltage, current or power. The breakdown of IGBT gate oxide would happen when the charge injection exceeds the threshold which is caused by accumulating of the temperature in the gate oxide when it is being operated [33].

Accelerated ageing approaches such as thermal cycling and electrical overstress are used in IGBT accelerated ageing experiments to speed up the degradation and failure of the IGBT in experimental environments which simulate the scenarios of industrial practical application. Precursor parameters, such as collector voltages, collector currents, gate voltages and currents, and environmental parameters such as temperature are monitored and recorded to be utilised for IGBT diagnosis and prognosis technology research [35].

Hardware experiment platform as shown in figure 4-1 is used in IGBT accelerated ageing experiments, and various experiment scenarios are simulated. Accelerated ageing stresses such as thermal cycling and electrical overstress are injected to stimulate the failure of IGBT happened in shorter operating time [20]. Failure mechanism and failure mode could be analysed by researchers after considerably shorter running time than that in practical application, and precursor parameters would also be selected and adopted. The running to failure data, which are used to analyse and develop the prognostics algorithm. Hence, IGBT accelerated ageing experiments are advantageous to the investigation and development of IGBT prognostics algorithm.

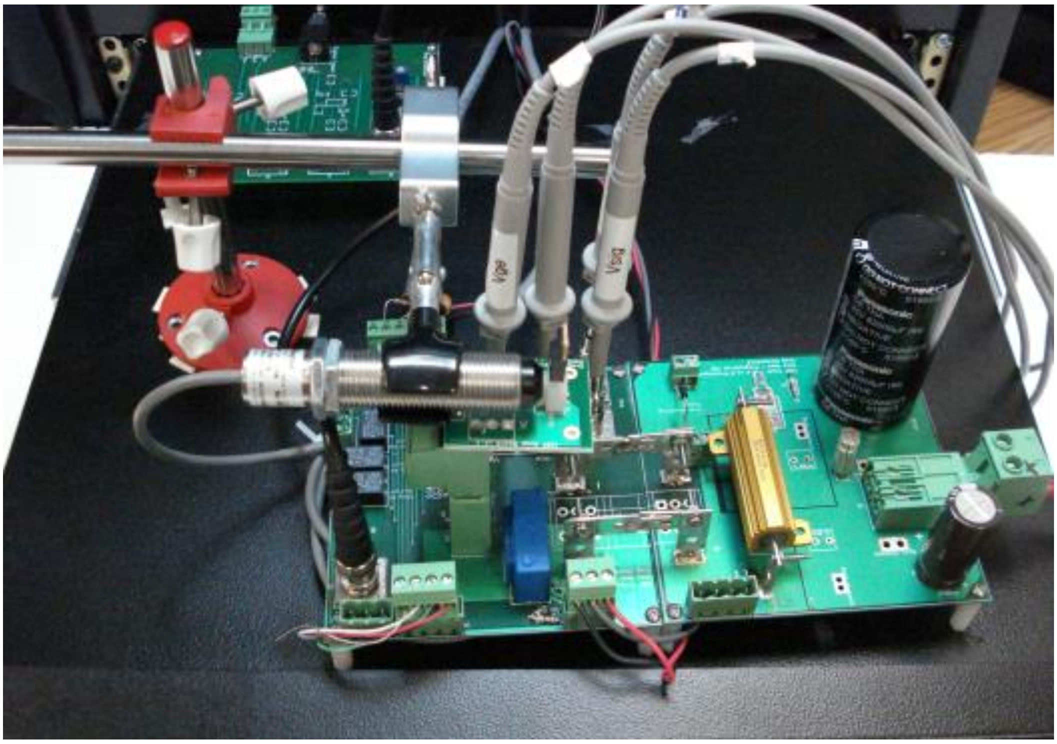

Figure 4-1 IGBT accelerated ageing experiments hardware [32]

Ames laboratory of NASA provided a series of standards for IGBT accelerated ageing experiments and the platform designing, the experiments data and measurements are shared in the website of NASA as an open databases used in developing prognostics algorithm for researchers in the world [32].

IGBT accelerated ageing data sets are measurements and sensor data collected from IGBT accelerated ageing experiment platform, which include the measurements being recorded from IGBT experimental (or operating) environment and survey data representing the deterioration of IGBT in the experiments. The data sets from NASA contain mass data from thermal overstress ageing experiments, including several parameters being recorded continuously such as collector current, collector voltage, gate voltage, package temperature etc. [34]. These data and parameters are monitored and recorded constantly until the IGBT failure in accelerated ageing experiments. The data sets are formatted in a data array which could be read by Matlab to facilitate analysis and processing for the data in the subsequent research and investigation. Prognostics algorithm would be developed with these data as samples and research objects.

As shown in the following figure 4-2, the process of the prognostics algorithm development is indicated. Firstly, IGBTs are tested in accelerated ageing experiments following standard experiment procedures in an environmental simulation scenario to accelerate ageing and failure. The monitoring data and experiments parameters are recorded and collected to transport into the software platform which are used as data formation and data storage. IGBT diagnostic and prognostics investigation will based on these data sets. Prognostics algorithm for RUL prediction will be developed, and Monte Carlo simulation will be utilised in the algorithm and which will be elucidated in the subsequent chapters.

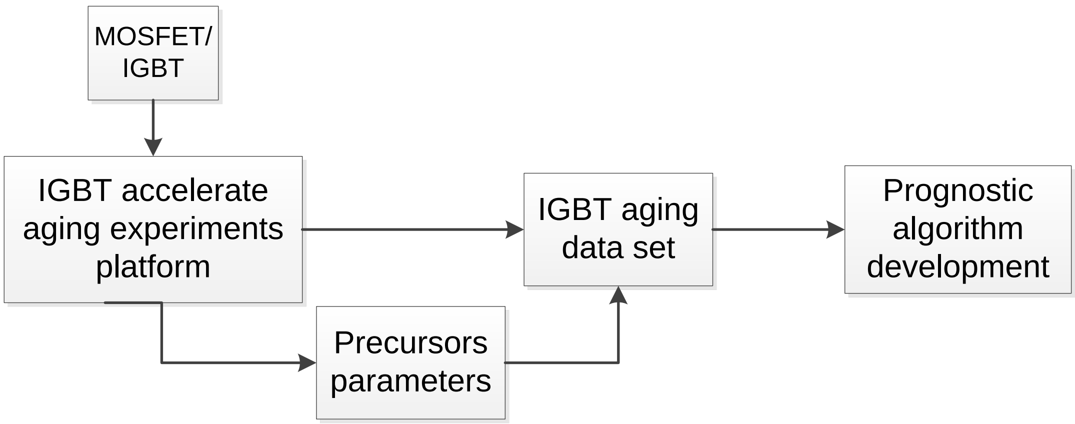

Figure 4-2 Process of IGBT prognostics algorithm development

Currently, IGBTs are widely used in the field of industrial control, such as automotive, motor drive and railway traction systems [28], the IGBT failure modes and degradation mechanism were investigated and researched extensively. For instance, Patil et al. [26] studied IGBT deterioration characterization and failure mode mechanism. As shown in figure 4-3, it is an IGBT with extreme damage in IGBT faults analysis experiment. However, Prognostics algorithm development is still the bottleneck in the domain of Prognostics and health management system, and which reduced the application in industrial domain of health management monitoring technology. Hence, the investigation focusing on the prognostics algorithm development and algorithm comparison analysis highlights its importance and significance. IGBT ageing data sets are utilised to diagnose and predict the RUL, and algorithm for estimation of IGBT RUL will also use them as valuable research resource.

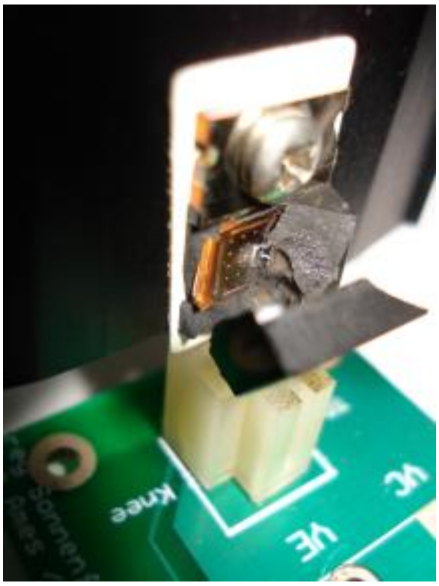

Figure 4-3 IGBT faults analysis experiment [32]

IGBT accelerated ageing experiments system includes hardware and software to induce failure, simulate scenario, control the progress of the experiments and record the experiments data. Sonnenfeld et al. [33] developed and defined the experimental test platform and requirements. Figure 4-4 shows the schematic of the IGBT Accelerated Ageing System (AAS). The hardware consists of a 300MHz Agilent DSO5034A oscilloscope with 1ns sample time and 1MB memory, a 20 MHz Agilent 33220A function generator for generating gate signals, a National Instruments PCI-6229 data acquisition and source card, a input/output connector block containing SCC-TC02 thermocouple measurement modules, a Agilent 6652A 25A/20V DC programmable power supply and a PC with LabVIEW [28].

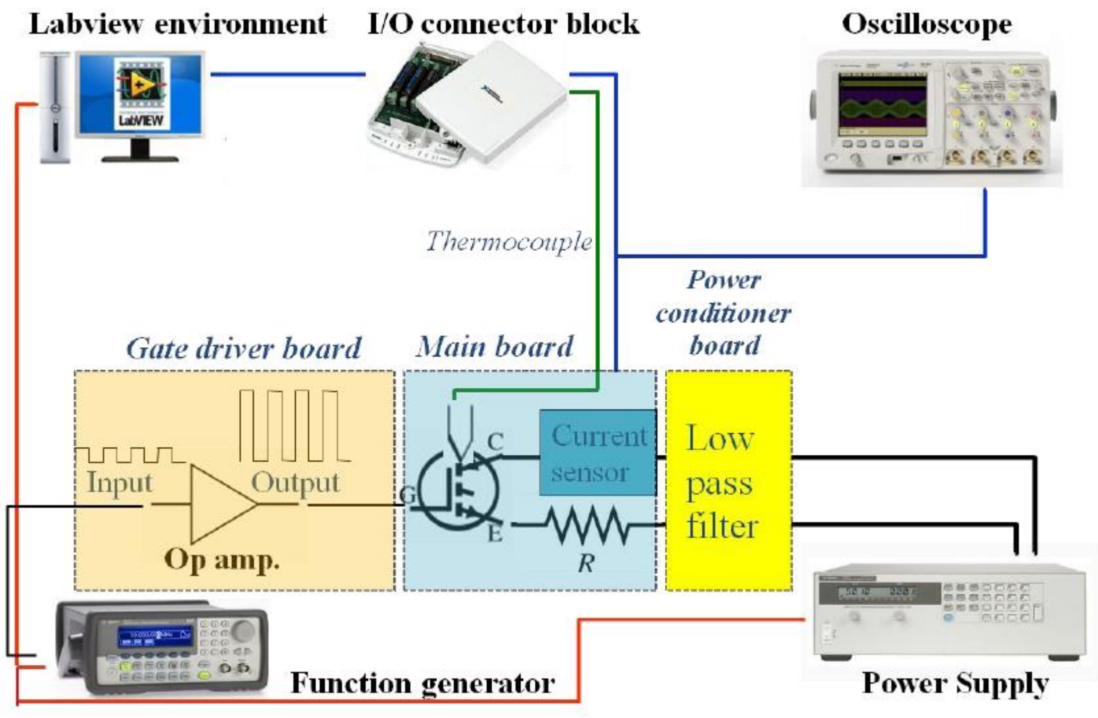

Figure 4-4 IGBT accelerated ageing system [20]

The ageing software consists of programs to control the ageing process, initiate and record measurements, and shut the system down upon device failure [26].

The schematic of the ageing process used to age the IGBTs in this study is shown in Figure 4-5. The IGBTs were power cycled under a resistive load with a predefined frequency, duty cycle, gate voltage and collector-emitter voltage. The device switching was controlled by temperature limits. The device under test was switched on and off using a function generator. The device temperature increased with switching as a result of conduction and switching losses. When the temperature rose beyond a pre-set level T_{max}, device switching was stopped. Switching was resumed again when the temperature fell below a pre-set value of T_{min}. No external heat-sink was attached to the device and no external cooling was provided.

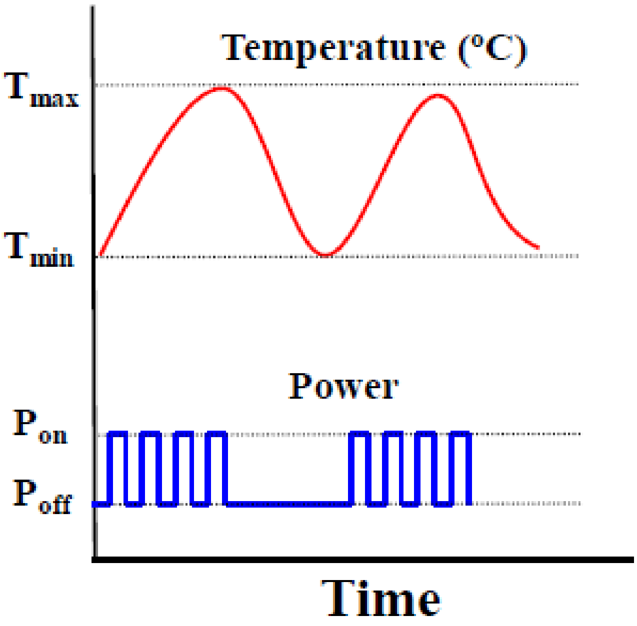

Figure 4-5 Schematic of the ageing process [20]

Labwiew programs/subroutines are called virtual instruments (VIs). Two Labview virtual instruments (VIs) were developed. The first VI, called the ageing VI was used to control the function generator based on temperature measurements. The second VI called the data storage VI was used to acquire and store voltage, current and temperature data.

The data storage VI stores data into a Matlab structured array file. The Matlab structure array is shown in Figure 4-6. The benefit of a structure array is the ability to store information of different data types within a given array.

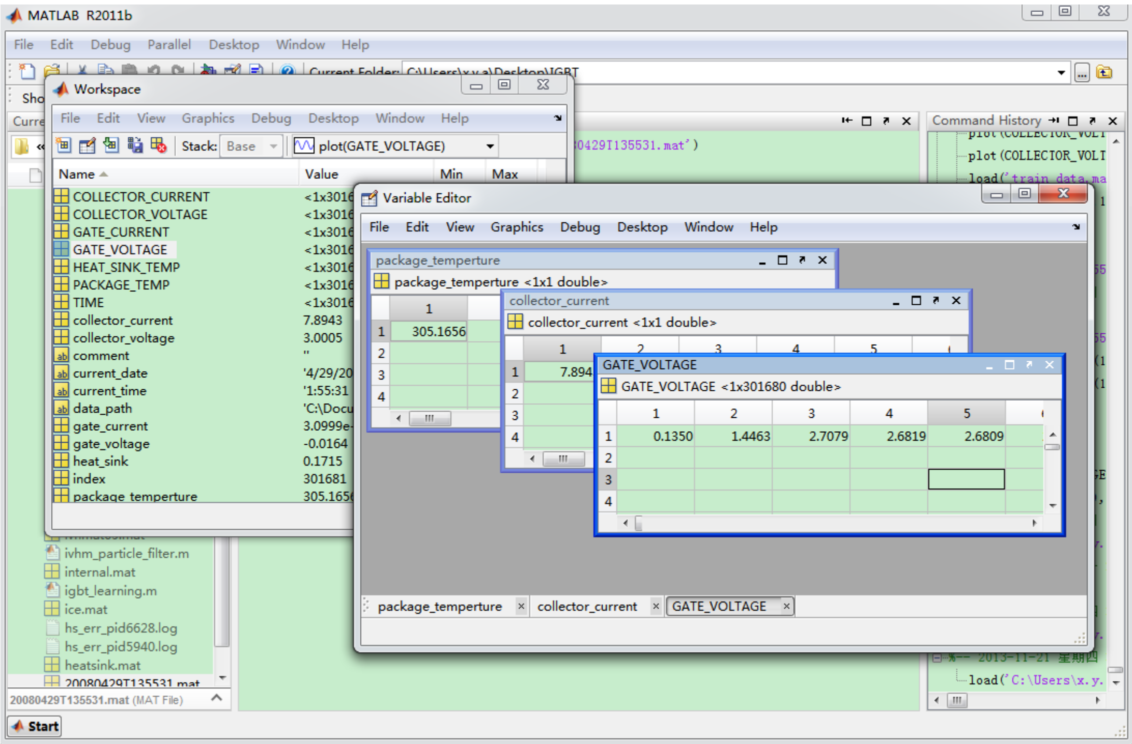

Figure 4-6 Matlab structure array

4.1.2 IGBT Prognostics Data set

IGBT ageing data set contains several device parameters that are monitored including the gate-emitter voltage (V_{GE}), collector-emitter current (I_{CE}), collector-emitter voltage (V_{CE}) and case and package temperatures. The data are stored in a structure array that is compatible with Matlab [32]. This allows for easy interface with diagnostic and prognostics algorithms that are developed using Matlab. As shown in figure 4-6.

IGBT ageing data set was acquired from the standard IGBT accelerated ageing experiments procedures. Ames laboratory of NASA collected and shared all ageing data surveyed in the standard ageing experiments donated by various universities, agencies and companies. In this thesis, the study of IGBT prognostics algorithm for prediction of remaining useful life is also based on the ageing data set from NASA [33].

The IGBT ageing data provided by Ames laboratory of NASA contain different sets of data collected from thermal overstress accelerated ageing experiments.

These ageing data were surveyed and recorded from the IGBT accelerated ageing experiments following the standard test procedures which were defined in literature [33].

The figure 4-7 shows the package temperature variation during the IGBT degradation in the ageing experiment. As the thermal cycling stress is induced into the IGBT experiment system, the package temperature indicates a cycling vibration following a certain plus frequency. At first the package temperature fluctuates between about 268℃ and 272℃, but the amplitude of the package temperature fluctuation increases from the 299000th time unit until the IGBT becomes fail. The temperature of the package increases constantly and the ageing experiment is stopped when the IGBT fails [34].

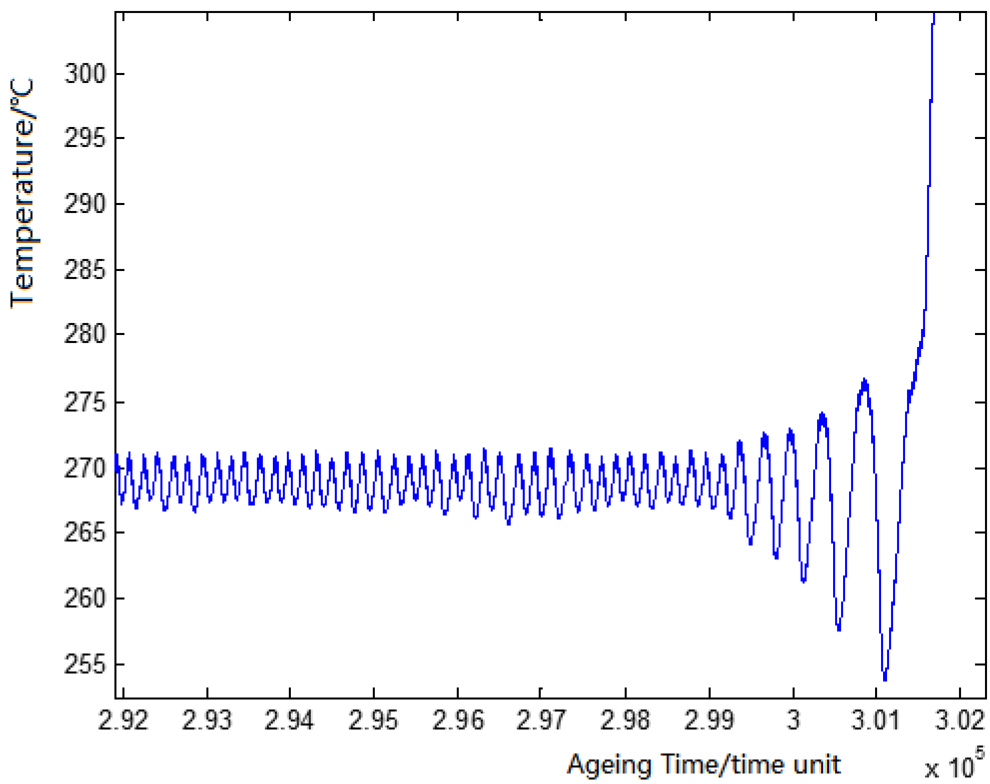

Figure 4-7 Temperature measurements in the ageing experiments [33]

As shown in figure 4-8, the IGBT collector emitter currents (I_{CE}) data is recorded. The profile indicates that the I_{CE} waves in a form of plus during the ageing process, and the I_{CE} plus interval begins to increase gradually when the

IGBT is going to fail, the features of which is similar to the change of the package temperature before the IGBT failure.

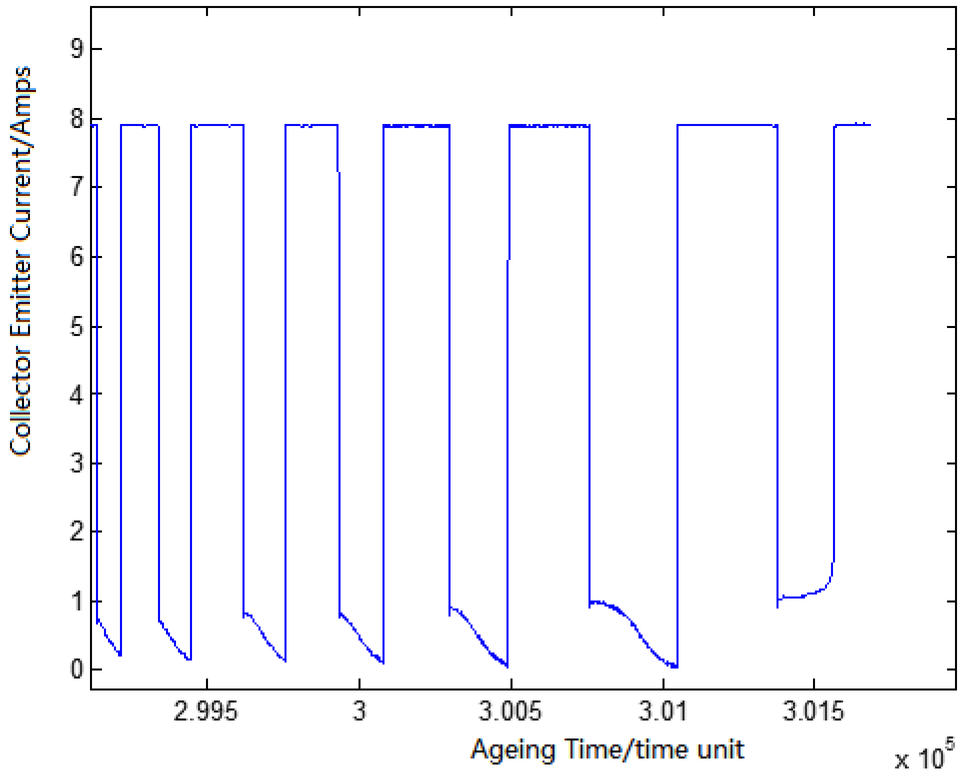

Figure 4-8 Currents measurements in the ageing experiments [33]

The IGBT ageing data recorded in the Matlab from the IGBT accelerated ageing experiments include parameters in table 4-1.

Table 4-1 IGBT ageing experiments parameters

Item	List of the ageing experiment parameters
1	Collector Current
2	Collector Voltage
3	Gate Current
4	Gate Voltage
5	Heat Sink Temperature
6	Package Temperature
7	Time

As shown in figure 4-7 and figure 4-8, the phenomena of which the package temperature and the collector emitter current indicating in profiles during the

IGBT degradation process before its failure reflect the harbinger features of the IGBT degeneration [35]. This kind of parameters could be used as precursor parameters in prognostics and diagnostics. In the study of this thesis, collector emitter voltage (V_{CE}) is used as precursor parameter in IGBT prognoses to predict the RUL and develop the prognostics algorithm.

4.2 Data Analysis of Degradation Process

4.2.1 Data Processing

The aim of data processing is to gain useful information from the data with the approach of analysis and sorting [21]. In this thesis, the IGBT ageing data V_{CE} are processed by the K-means clustering method which is presented in the literature [35] and Alghassi has described and processed the ageing data in state-based prognostics models. In this study, the research will be based on these processed data.

Collector emitter voltage is utilised as precursor parameter for the IGBT ageing prognostics in this study, the profile of the V_{CE} collected from the ageing experiment is presented in figure 4-9. The collector emitter voltage of the IGBT presents a monotonically increasing in the whole ageing process and the V_{CE} also presents a fluctuation and oscillation during this process [36], but the V_{CE} falls quickly at the end of the ageing process when the IGBT fails. The overall ageing process is more than 10000 time units.

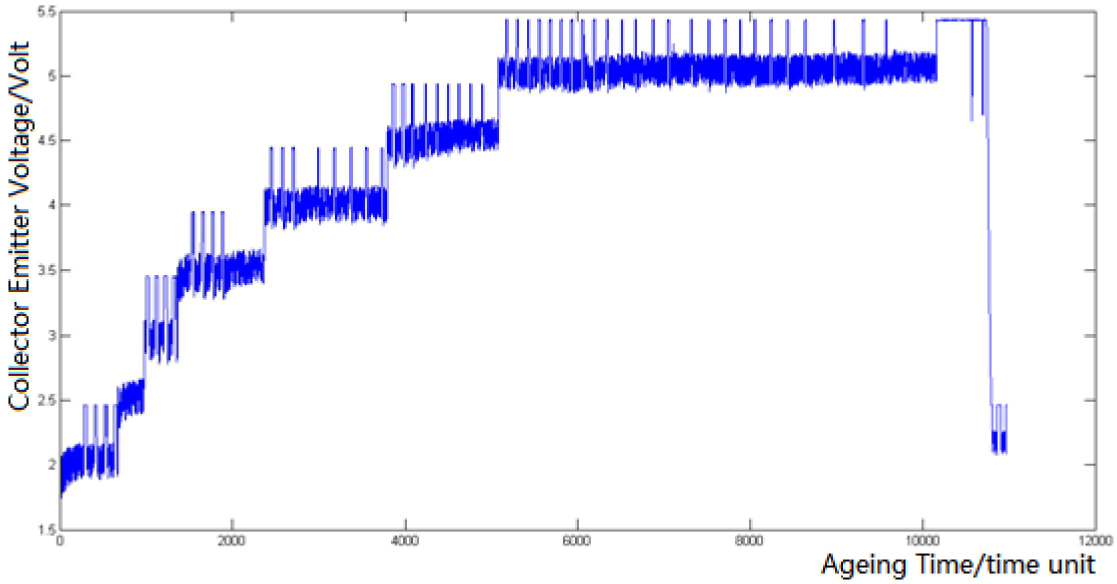

Figure 4-9 Collector emitter voltage profile before processing

The ageing data of collector emitter voltage as precursor parameter are processed by K-mean clustering method. As shown in figure 4-10, the K-mean clustering method includes 2 steps, clustering and cluster evaluation.

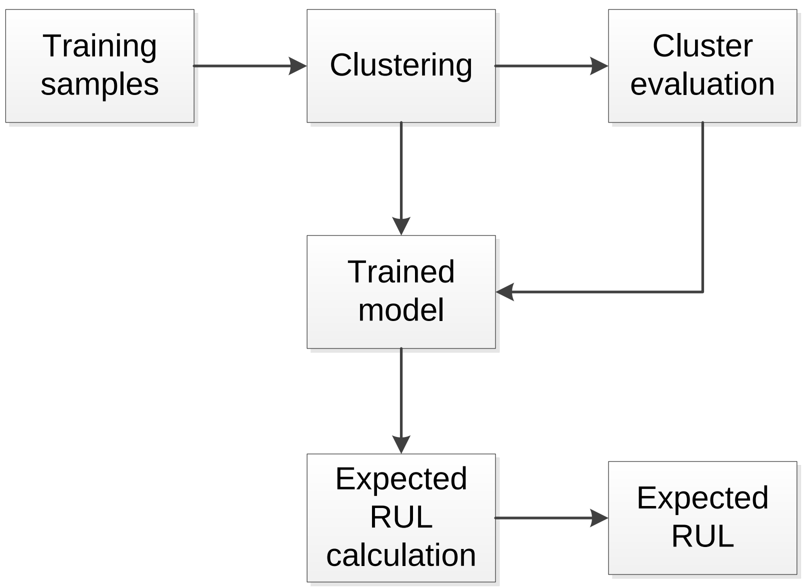

Figure 4-10 K-mean data processing method [35]

The computing formula is present as equation 4-1. Alghassi [35] has described this method in detail and the research in this thesis will be based on the result of this work.

$$\mathrm{CH} = \left[\frac{\sum_{C=1}^{k} n_C \|z_C - z\|^2}{k-1}\right] \Big/ \left[\frac{\sum_{C=1}^{k} \sum_{i=1}^{n_C} \|x_i - z_C\|^2}{n-k}\right] \quad \textbf{(4-1)}$$

Where CH is the evaluation parameter in the K-mean clustering method which is defined by Calinski-Harabasz (CH)

k is the number of clusters in k-means clustering

z_c is the cluster validity index

x is the given data for clustering

The figure 4-11 shows the profile of the V_{CE} after being processed with the K-mean method. As shown in the figure the voltage of the V_{CE} presents an increase step by step during the whole IGBT ageing process. It is much easier to analyse the IGBT degeneration process by the ageing data V_{CE} after being processed. The variation of the V_{CE} voltage in the whole ageing process could be separated into seven stages, and the V_{CE} voltage of each stage is different.

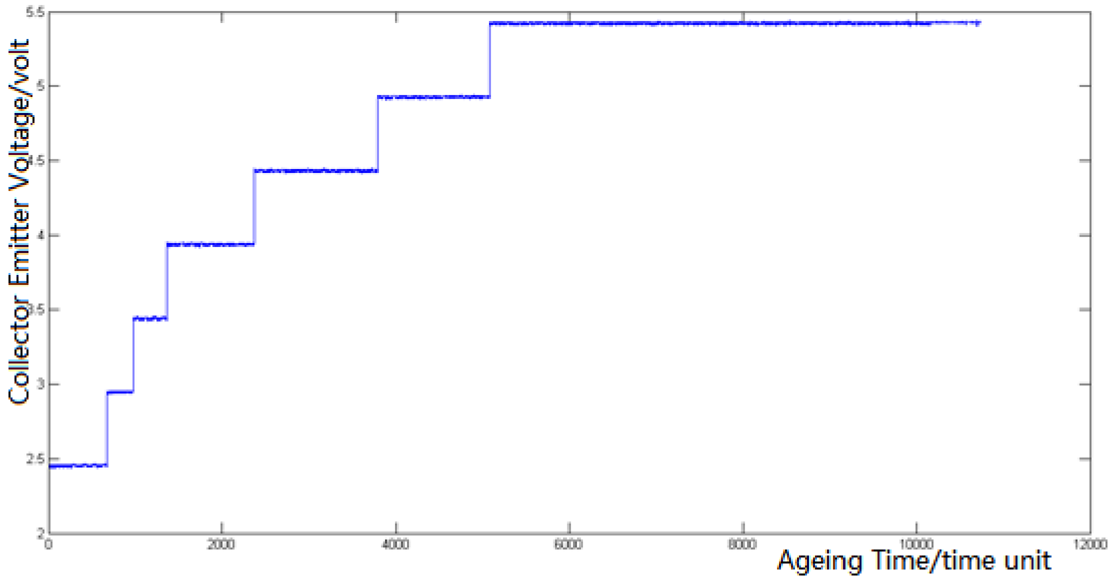

Figure 4-11 Collector emitter voltage profile after processing

In this study, seven IGBTs have been researched and analysed, and seven IGBTs ageing data were processed. According to the K-mean method, the seven IGBTs V_{CE} processed data were computed in Matlab. From figure 4-11, seven stages are separated from the whole IGBT ageing process, and the duration times for which the IGBT V_{CE} stays in each stage are computed and listed in table 4-2. This data will be used in IGBT prognostics and RUL prediction.

Table 4-2 IGBT data processing result

	IGBT degradation process						
IGBT No.	1st phase failure time (time unit)	2nd phase failure time (time unit)	3rd phase failure time (time unit)	4th phase failure time (time unit)	5th phase failure time (time unit)	6th phase failure time (time unit)	Failure Time (time unit)
1	670	970	1368	2369	3793	5079	10740
2	827	827	1389	1389	2306	3208	5075
3	1099	1099	1905	2490	2900	3889	6799
4	894	894	1733	2384	2789	3887	5141
5	927	1055	2115	2544	3388	7449	10285
6	578	578	1560	2109	3403	4236	12164
7	750	1631	2755	3001	3757	5079	6861

time unit: represents time durations at a given unit in the experiments

4.2.2 IGBT Degradation

Because there are many uncertain factors effecting the quality of IGBT during the process of IGBT manufacturing and packaging, the IGBT may have various uncertain and potential defects after the completion of IGBT producing due to these uncertain factors. The defects are the main cause which results in the ageing and failure in the process of working. Table 4-3 lists the main IGBT internal fault making the IGBT degeneration in using. Due to the uncertainty and randomness of internal defects in IGBT, the failure of the IGBT is random and the ageing and degeneration process of the IGBT are also uncertain and random.

Table 4-3 IGBT fault modes

Item	Fault Mode
1	Thermal Runaway
2	Latch Up
3	Dielectric Gate Breakdown
4	Collector/emitter degradation
5	Piping/Contact Migration

4.2.3 Degradation Profile

As shown in figure 4-12, it indicates the profile of the IGBT collector emitter voltage in the whole process of the IGBT degradation. The voltage of the V_{CE} presents an increase step by step during the whole IGBT ageing process. The variation of the V_{CE} voltage in the whole ageing process could be separated into seven stages, and the V_{CE} voltage of each stage is different.

The voltage of the V_{CE} starts at about 2.45V at the beginning of the ageing process, and the whole process is separated into seven phases according to the variation of the $V_{CE.}$ Then the voltage of the V_{CE} increases about 0.5V each time phase by phase, but within each phase the voltage of the V_{CE} basically keeps at a constant level with littler fluctuation.

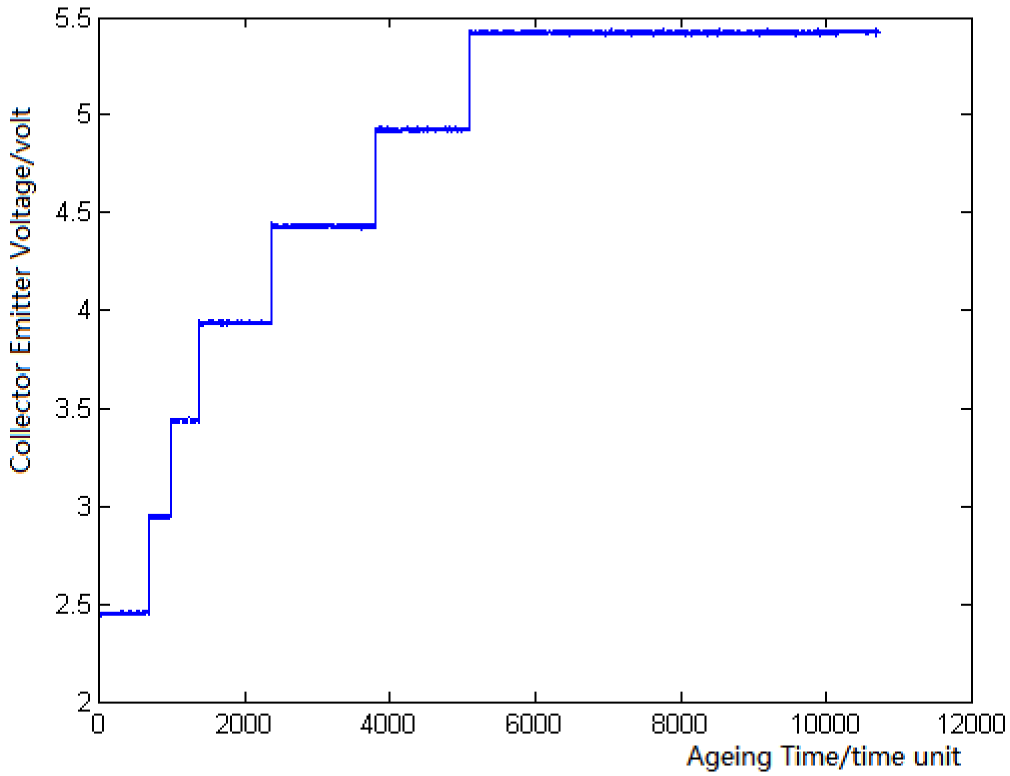

Figure 4-12 IGBT degradation profile

Hence, according to the analysis of the IGBT V_{CE} profile, the IGBT degradation process could be separated into several phases based on the different voltage of the V_{CE}.

In this thesis, the IGBT process will be defined as 6 phases, and when the voltage of V_{CE} increases at 5.45V the IGBT fails. The research and prognostics in this thesis will be based on this.

After data processing, the duration of each degeneration phase for IGBT No.1 is listed in table 4-4

Table 4-4 IGBT degeneration phase

	IGBT Degradation Process					
Degradation Phase	1st	2nd	3rd	4th	5th	6th
Collector Emitter Voltage	2.45V	2.95V	3.45V	3.95V	4.45V	4.95V
Duration Time (time unit)	670	300	398	1001	1424	1286

time unit: represents time durations at a given unit in the experiments

4.3 Modelling IGBT Degradation Profile

4.3.1 IGBT Degradation Modelling

IGBT Degradation Modelling is to utilise the IGBT ageing data according to the probability of statistical distribution to establish the stochastic statistical model, which is used to predict the remaining useful life of IGBTs [38].

IGBT degradation process is considered to be random and the process of IGBT deterioration could be described by the numbers in table 4-5 after the data processing, and the table 4-5 indicates the IGBT degradation of the whole run to a failure. As shown in the table, there are 7 IGBTs ageing data, the process for the IGBT degradation of running-to-fail is separated into 6 steps, and each number in the table represents the duration of the step. In other words, before the IGBTs completely fail, the IGBTs would deteriorate and undergo 6 degeneration phases, and each phase sustains a period until the IGBTs continue to degenerate into the next degradation phase. The IGBTs would completely fail when they have finished the whole six degeneration phases. After the data processing, the time spans of six degeneration phases are recorded in table 4-5. Take the first IGBT for example, the operational useful life of IGBT-No.1 is 5079 time units, and the duration of the IGBT staying in its first degeneration phase is 670 time units, then the IGBT downgrades into the second degeneration phase and stays 300 time units before its further degeneration to step into the third degeneration phase. And so on, until the IGBT has stayed for 1286 time units in the last phase, the IGBT continues to degrade and becomes a complete failure.

Table 4-5 IGBTs degradation phases

	Duration of Each Phase						
IGBT No.	1st layer duration time (time unit)	2nd layer duration time (time unit)	3rd layer duration time (time unit)	4th layer duration time (time unit)	5th layer duration time (time unit)	6th layer duration time (time unit)	IGBT life (time unit)
1	670	300	398	1001	1424	1286	5079
2	827	0	562	0	917	902	3208
3	1099	0	806	585	410	989	3889
4	894	0	839	651	405	1098	3887

5	927	128	1060	429	844	4061	7449
6	578	0	982	549	1294	833	4236
7	750	881	1124	246	756	1322	5079

time unit: represents time durations at a given unit in the experiments

According to the characterization of the IGBT and the mechanism of failure, the occurrence of the IGBT degeneration is random. In other words, the time duration of each degradation phase is considered to be random and follow a stochastic statistical probability distribution. Hence, the IGBTs degradation models are established from these considerations, and RUL prediction would be based on the degradation models. The durations of each IGBTs degeneration phase are utilised as samples to build stochastic models, specifically, the whole process of IGBT running-to-fail has 6 steps and IGBTs become failed until which have degenerated total 6 degeneration phases. 6 independent stochastic process models could be built to represent the homologous degeneration phases which follow the random statistical probability distribution. In this thesis, Gamma distribution, Exponential distribution and Poisson distribution are utilised in the degradation modelling.

As shown in figure 4-13, the IGBT degeneration and failure are considered to be random, so the duration time (T_i) of the degeneration phase is considered to be a random variable. The y-axis in the figure represents the collector emitter voltage of the IGBT, and the x-axis represents the ageing time of the experiment. The figure indicates that the duration time (T_i) in which the IGBT was measured in different voltage of V_{CE} is a random variable and it could be represented by the stochastic statistical probability models. The probability distribution function could be represent by equation 4-2.

$$\mathrm{F}(T_i \leq \mathrm{x}) = \mathrm{P} \qquad \textbf{(4-2)}$$

Where p is the probability of the distribution

T_i is the duration time (time unit)

x is the random variable

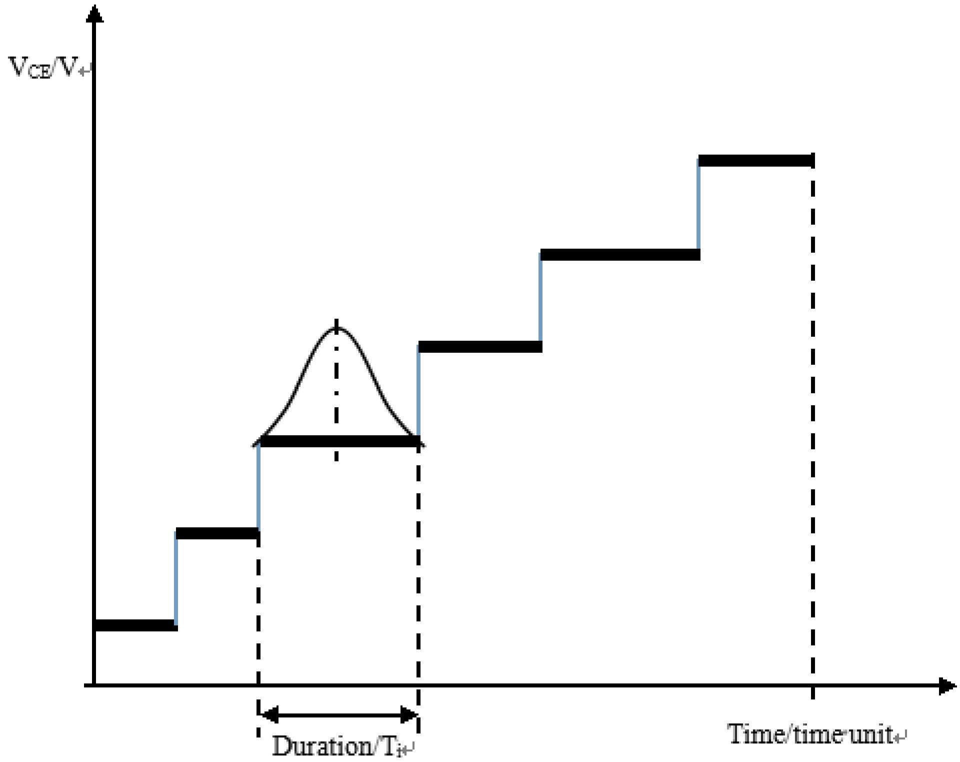

Figure 4-13 IGBT degeneration phase

As shown in figure 4-14, the IGBT degradation process is separated into 6 phases, the duration time (T_i) of each phase is an independent random variable. Hence, the whole IGBT ageing process could consist of 6 independent stochastic distribution models.

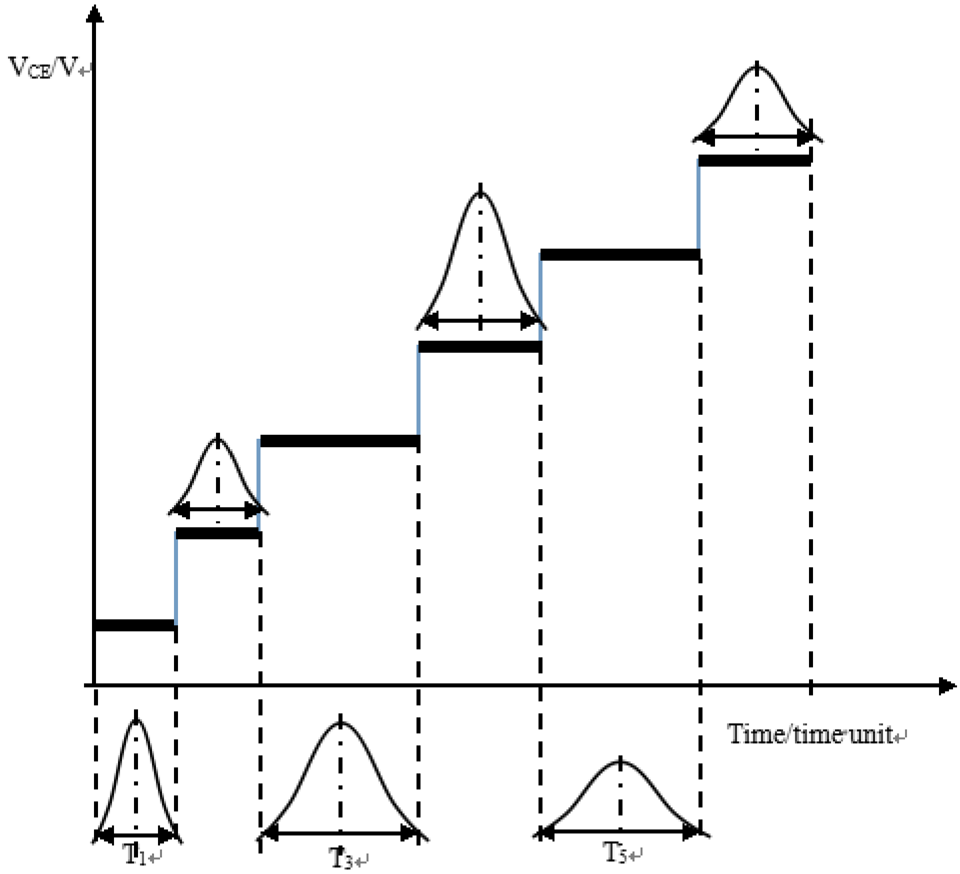

Figure 4-14 IGBT degradation models

4.3.2 Gamma Model

Gamma Model is a degradation model that uses the Gamma probability distribution to develop prognostics algorithm to predict the RUL of IGBTs. During the whole process of IGBT degeneration, the IGBT operational time in each degeneration phase follows the Gamma probability distribution. In other words, the duration time (T_i) of the IGBT degeneration phase is a random variable with a Gamma distribution.

The probability density function of the Gamma distribution is:

$$f(x) = x^{k-1}\left(e^{\frac{-x}{\theta}} \Big/ \Gamma(k)\theta^{k} \right) \tag{4-3}$$

Where κ is the shape parameter and θ is scale parameter, so that the duration time (Ti) of the IGBT degeneration phase could be represented by equation 4-4:

$$f(T_i = x) = P = x^{k-1}\left(e^{\frac{-x}{\theta}} \Big/ \Gamma(k)\theta^k\right) \tag{4-4}$$

Where T_i is the duration time of the IGBT degeneration phase (time unit)

x is the random variable

P is the probability of the distribution

The profile of the Gamma probability density function is shown in figure 4-15.

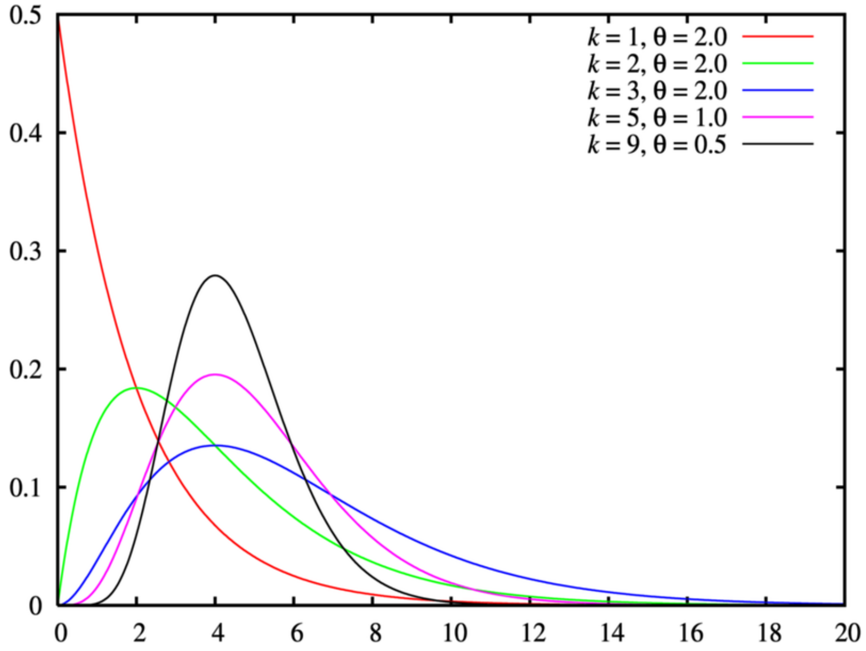

Figure 4-15 Gamma distribution [36]

4.3.3 Exponential Model

Exponential Model is a degradation model that uses the Exponential probability distribution to develop prognostics algorithm to predict the RUL of IGBTs. During the whole process of IGBT degeneration, the IGBT operational time in each degeneration phase follows the Exponential probability distribution. In other words, the duration time (T_i) of the IGBT degeneration phase is a random variable with an Exponential distribution.

The probability density function of the Exponential distribution is:

$$f(x) = \lambda e^{-\lambda x} \quad \textbf{(4-5)}$$

Where λ is the parameter of the distribution, so that the duration time (Ti) of the IGBT degeneration phase could be represented by equation 4-6

$$f(T_i = x) = \lambda e^{-\lambda x} \quad \textbf{(4-6)}$$

Where T_i is the duration time of the IGBT degeneration phase (time unit)

x is the random variable

The profile of the Exponential probability density function is shown in figure 4-16.

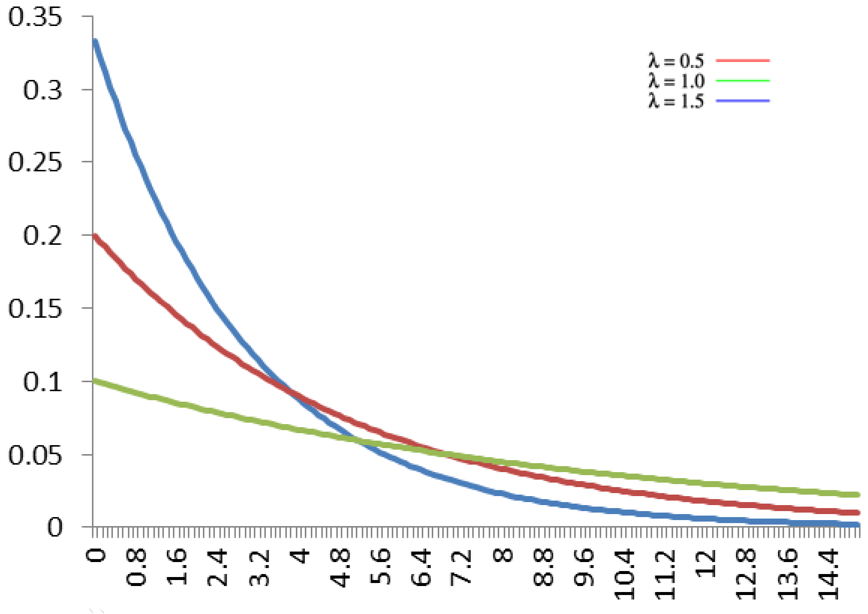

Figure 4-16 Exponential distribution [36]

4.3.4 Poisson Model

Poisson Model is a degradation model that uses the Poisson probability distribution to develop prognostic algorithm to predict the RUL of IGBTs. During the whole process of IGBT degeneration, the IGBT operational time in each degeneration phase follows the Poisson probability distribution. In other words, the duration time (T_i) of the IGBT degeneration phase is a random variable with a Poisson distribution.

The probability density function of the Poisson distribution is:

$$f(x) = \frac{e^{-\lambda}\lambda^k}{k!} \tag{4-7}$$

Where λ is the parameter of the distribution, so that the duration time (Ti) of the IGBT degeneration phase could be represented by equation 4-8

$$f(T_i = x) = \frac{e^{-\lambda}\lambda^k}{k!} \tag{4-8}$$

Where T_i is the duration time of the IGBT degeneration phase (time unit)

x is the random variable

The profile of the Poisson probability density function is shown in figure 4-17.

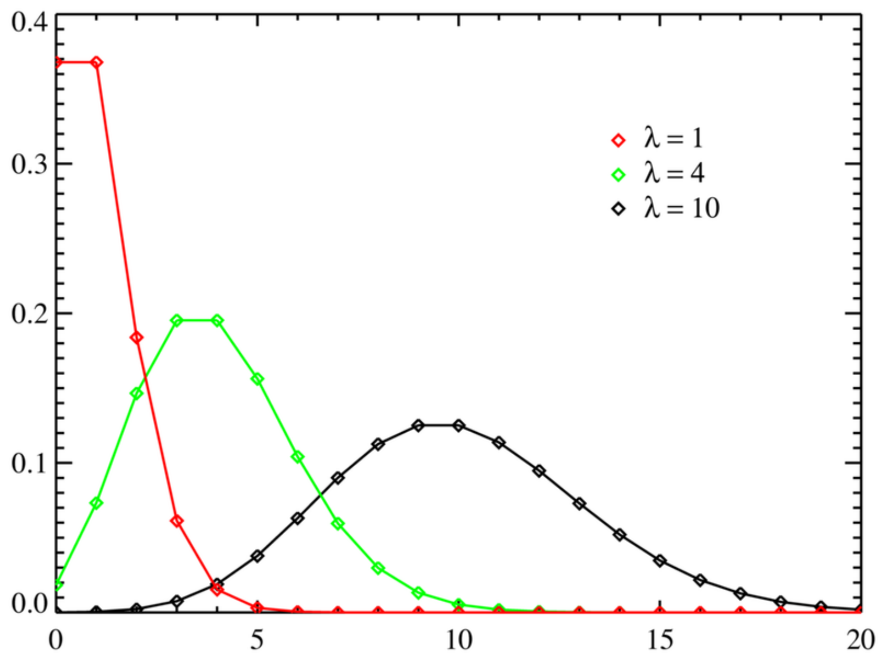

Figure 4-17 Poisson distribution [36]

4.4 Maximum Likelihood Estimation

4.4.1 Model Parameters

There are unknown parameters to be determined in the Gamma models, Exponential models and Poisson models. The Maximum Likelihood Method is used to calculate the model parameters. Table 4-6 lists the parameters of each model.

Table 4-6 Model parameters

Item	Models	Parameters
1	Gamma	κ, θ
2	Exponential	λ
3	Poisson	λ

In order to calculate the model parameters, the duration times of seven IGBTs in degradation process are used as statistical samples, and the six degradation phases are independent stochastic process. According to the maximum likelihood method, the parameters of the models could be estimated and determined.

4.4.2 Gamma Model

There are two modelling parameters, κ and θ which should be figured out in the Gamma distribution, and the IGBT degradation process consists of 6 degradation phases, the duration of each phase is an independent stochastic process following the Gamma probability distribution in Gamma modelling. Hence, there are 6 different sets of Gamma modelling parameters which consist of κ and θ. According to the maximum likelihood method.

$$\mathrm{L}(\kappa, \theta) = \prod_{i=1}^{n} f(x_i, \kappa, \theta) \tag{4-9}$$

From which the estimators of κ and θ are:

$$\hat{\theta} = \frac{1}{\kappa N} \sum_{i=1}^{N} x_i \tag{4-10}$$

$$\hat{\kappa} \leftarrow \kappa - \frac{\ln(\kappa) - \psi(\kappa) - s}{\frac{1}{\kappa} - \psi'(\kappa)} \tag{4-11}$$

As listed in table 4-7, we also could calculate the Gamma distribution parameters using Matlab's maximum likelihood function for the 6 independent models of the IGBT degradation. These 6 models present the 6 independent degeneration phases of the whole IGBTs ageing process.

Table 4-7 Gamma models parameters

Parameter	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
κ	25.77	0.0883	9.3663	0.2818	5.1662	3.3289
θ	31.8	211.67	88	1754.4	167.3	450.2

4.4.3 Exponential Model

There is only one modelling parameter λ which should be figured out in the Exponential distribution, and the IGBT degradation process consists of 6 degradation phases, the duration of each phase is an independent stochastic process following the Exponential probability distribution in Exponential modelling. Hence, there are 6 different Exponential models. According to the maximum likelihood method.

$$\hat{\lambda} = \frac{1}{\bar{x}} = \frac{n}{\sum_{i=1}^{n} x_i} \tag{4-12}$$

As listed in table 4-8, we can also calculate the Exponential distribution parameter using Matlab's maximum likelihood function for the 6 independent models of the IGBT degradation.

Table 4-8 Exponential models parameter

Parameter	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
λ	820.7	187	824.4	494.4	864.3	1498.7

4.4.4 Poisson Model

There is one modelling parameter λ which should be figured out in the Poisson distribution, and the IGBT degradation process consists of 6 degradation phases, the duration of each phase is an independent stochastic process following the Poisson probability distribution in Poisson modelling. Hence, there are 6 different Poisson models. According to the maximum likelihood method.

$$\hat{\lambda} = \frac{1}{\bar{x}} = \frac{n}{\sum_{i=1}^{n} x_i} \tag{4-13}$$

As listed in table 4-9, we also could calculate the Poisson distribution parameter using Matlab’s maximum likelihood function for the 6 independent models of the IGBT degradation.

Table 4-9 Poisson models parameter

Parameter	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
λ	820.7	187	824.4	494.4	864.3	1498.7

4.5 Monte Carlo Simulation

Monte Carlo Simulation approach is used to simulate the IGBT degradation process in this thesis, and it is also utilised to develop the prognostics algorithm to predict the RUL of IGBTs. In chapter 4.3, IGBT degradation process has been treated mathematically by modelling with stochastic statistical probability distribution. The whole IGBT degradation process is separated into 6 degeneration phases. Each phase is modelled as an independent random statistical model and the duration time (Ti) of each phase follows the probability distribution. Hence, Monte Carlo simulation could be utilised to generate the random number following the stochastic probability distribution to simulate the IGBT degeneration phases.

The approach which utilises the Monte Carlo method to simulate the IGBT degradation process is described: firstly, the IGBT degradation models have been built in chapter 4.3, and the modelling parameters have been calculated in chapter 4.4 with maximum likelihood method. Secondly, the Monte Carlo simulation is used to generate the duration time of each IGBT degradation phase according to the statistical distribution of the modelling. Specifically, when the IGBTs stay in the first phase of the degeneration, the degradation model of the first phase would be used by the Monte Carlo simulation to generate a random number to represent the duration time of IGBT would stay in the first degeneration phase. In the same way, the duration time of each six degradation phases of the whole IGBT degradation process would be simulated and generated by Monte Carlo method. In the following chapter, the prognostics algorithm and the prediction approach of the RUL estimation will be developed according to this simulation.

The Monte Carlo simulation in this thesis is implemented in Matlab. Firstly, the degradation models are established and the model parameters are calculated by the maximum likelihood estimation method, and, then, the random number function in Matlab is utilised to generate the random numbers that follow the stochastic probability distribution of the models. As these random numbers are generated following the distribution of the models, the degradation models are used to represent the degeneration phases, so the random numbers generated by the random function could be used to simulate the duration time of the degeneration phases.

5 IGBT Prognostics and RUL Prediction

5.1 Prognostics Approach

Prognostics is used to predict the remaining useful life (RUL), and this is one of the most significant goals for the prognostics system. It is also the aim to develop the algorithm of prognostics. Presently, the most prevailing prognostics approaches include data-driven methods and model-based methods [10]. Data driven prognostics methods utilise precursor data recorded by sensors, which are used to monitor the condition of the research object, to predict the future operating condition of the system. Relationship between sensor data and mechanism of degradation and fault will be analysed and utilised to forecast the healthy condition. Model based methods use modelling approach to predict the remaining useful life of the system.

There are several approaches that have been developed for electronic prognostics. A few examples of these prognostics approaches will be described here. The current state of research on prognostics of IGBTs will be discussed in detail. The issues unaddressed in previous IGBT prognostics studies will form the basis for the motivation of the current study.

Saha et al. [11] used a system model approach to estimate the remaining useful life of lithium ion batteries. The battery was represented by a lumped parameter model. The parameters of the model were calculated using relevance vector machine (RVM) regression on experimental data. An extended Kalman filter and particle filter algorithms were used to determine the battery RUL.

Goodman et al. [12] described the use of prognostics cells to predict failure in integrated circuits. The prognostics cell is developed to fail prior to the circuit on the same chip for all realistic operating conditions. Prognostics monitors in the test cell see the exact environment that the actual circuit sees, but at an accelerated rate, thereby providing failure prediction

Kumar et al. [13] used the data-driven approach to detect anomalies of notebook computers by monitoring performance parameters and comparing them against the historical data using Mahalanobis distance.

A physics-based prognostics approach was used by Cristaldi [14] in the development of a diagnostic system based on a virtual system. Using a Virtual Test Bed (VTB), system faults found in a real world system were simulated along with a normally operating real world system.

For the development of a fault diagnostic system for a brake-by-wire system, Murphey [15] used a similar fuzzy system approach. Six failure modes of the system were identified and three measurement points chosen. The input signals were processed on a segment-by-segment basis, by a feature extraction process, and by fault detection.

In this thesis, the prognostics approach is based on the degradation data to build the IGBT degeneration phase stochastic models which have been depicted in chapter 4, and then, Monte Carlo simulation is utilised to prognose and predict the RUL of IGBT. As shown in figure 5-1, it indicates the whole IGBT prognostics process in this study.

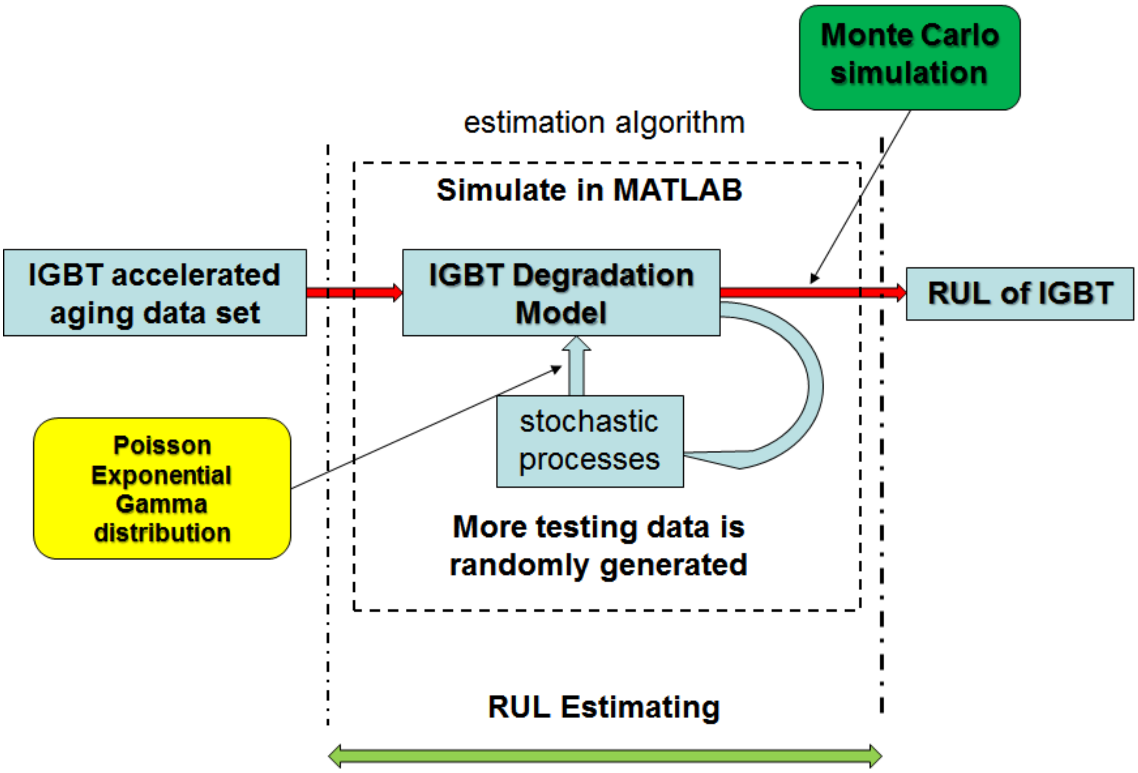

Figure 5-1 The IGBT prognostic

5.2 RUL Estimation for IGBTs

5.2.1 RUL Prediction

The RUL prediction is the main goal of this thesis, and according to the studying of the IGBT RUL prediction the prognostics algorithm is developed. Monte Carlo simulation and IGBT degradation modelling are combined to predict the remaining useful life of the IGBTs.

In chapter 4.3, the IGBT degradation models have been established which are based on the IGBT ageing data. According to the IGBT process profile described in chapter 4.2.3, the IGBT degradation process could be separated into 6 phases. The performance of IGBT would be more degenerated when the IGBT steps from one degeneration phase into a further degeneration phase. The IGBT degeneration could be detected and reacted by the V_{CE}. Specifically, the V_{CE} profile presents a jump step by step, the IGBT degradation leads the increase of the V_{CE} according to the mechanism of the IGBT degradation which is explained in chapter 4. When the IGBT stays in one degeneration phase, the V_{CE} fluctuates in a small range and the profile of the V_{CE} almost keeps a constant level, and when the V_{CE} increases by a step, then the IGBT degenerates into a new generation phase.

Monte Carlo simulation is utilised to generate the random numbers to represent the duration time of the IGBT generation phases according to the degradation models, and the V_{CE} which is detected and recorded from the IGBTs ageing experiment is used to judge the IGBT deterioration condition and degeneration phase.

In the process of Monte Carlo simulation, the random numbers are generated by Monte Carlo method according to the degradation models in chapter 4.3, and the stochastic distribution of the random numbers has the same statistical probability with the duration of the IGBT degeneration phases. Hence, the random numbers generated from Monte Carlo simulation could be utilised to represent the duration time of the IGBT degeneration phases. On the other hand, the IGBT collector emitter voltage (V_{CE}) which was monitored from the experiments is used to judge the IGBT degeneration phase, as the RUL computing method for different phase is not the same. As shown in figure 5-2, Monte Carlo simulation generates T_i following the probability distribution of the degradation models, the collector emitter voltage and the simulated T_i are the input variables of the RUL predicting algorithm, and the predicted RUL is the output.

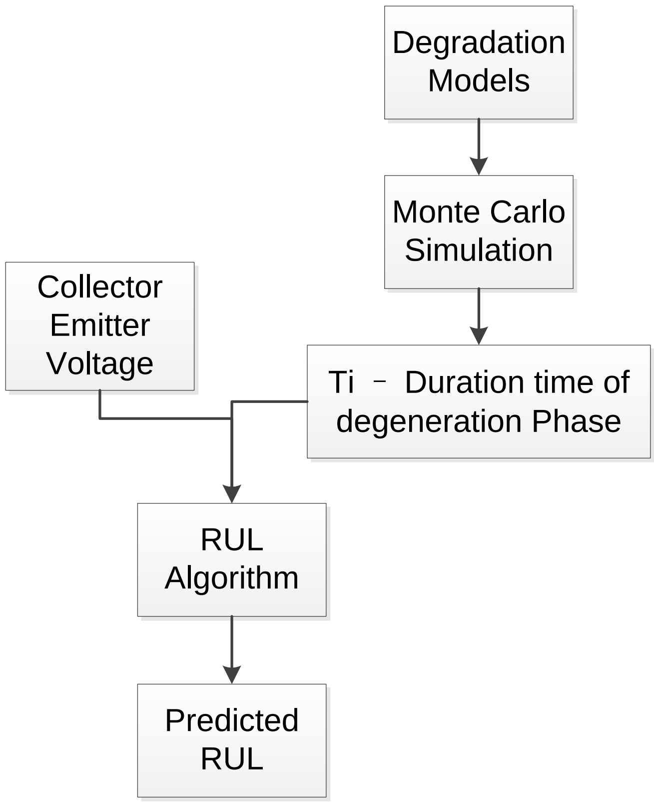

Figure 5-2 RUL predicting process

In the process of IGBT prognosis and RUL prediction, the collector emitter voltage is utilised to judge the IGBT degeneration phase. As shown in the figure 4-13, the IGBT degradation process is separated into 6 phases, the collector emitter voltage in each phase is different, and the mean value of the V_{CE} is shown in the table 4-4. On the other hand, the V_{CE} is monitored and recorded constantly by the sensors.

In this study, Gamma model, Exponential model, Poisson model and combining model were used to predict the RUL.

5.2.2 Gamma Distribution

Gamma model is to use Gamma distribution to develop the prognostics algorithm to predict the IGBT RUL.

The whole IGBT process is separated into 6 degeneration phases and 6 stochastic models are built based on the 6 degeneration phases. According to the study in chapter 4, the whole IGBT ageing process is modelled by 6 independent Gamma distribution models. Each model represents the relevant degeneration phase in the ageing process. As shown in figure 5-3, the ageing process includes 6 phases and each phase is an independent Gamma model, T_i means the duration time of the phase and the subscript i represents the ordinal of the degeneration phase. So T_i is a random variable of Gamma distribution in this model. S_i is the ending time of the degeneration phase in the sequence of i. *t* is the ageing time when the IGBT RUL prediction is being carried out.

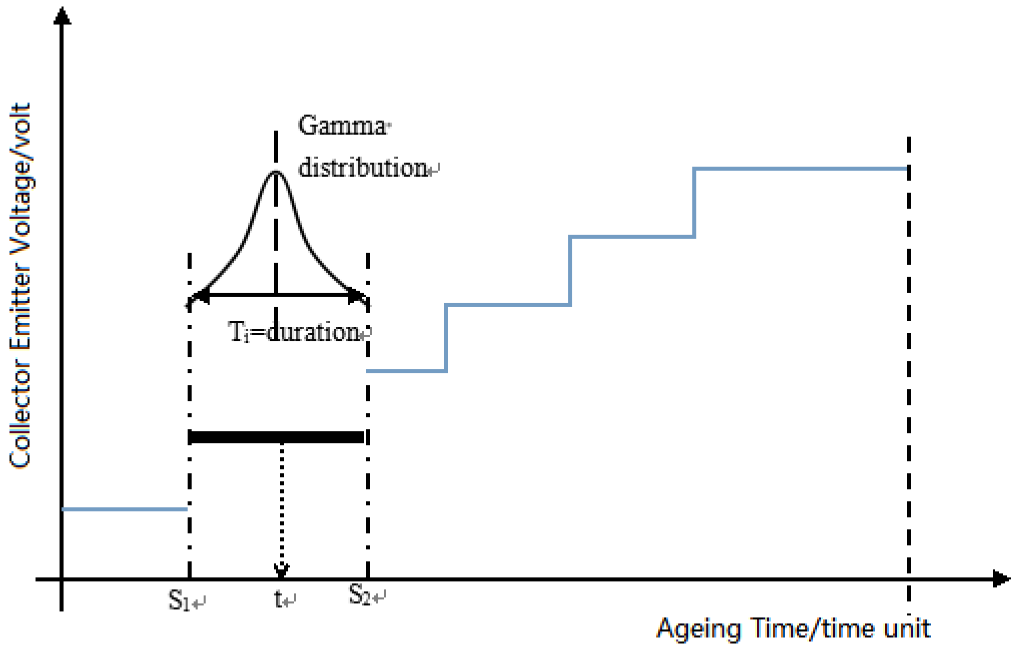

Figure 5-3 Gamma model to predict RUL

The RUL prediction could be indicated by the equation 5-1

$$RUL_P = S_f - t \tag{5-1}$$

Where RUL_P means the predicted RUL by Gamma model (time unit)

S_f is the predicted IGBT failure time in the ageing process (time unit), it is also the ending time of the last degeneration phase

t is the ageing time in the accelerated ageing experiment (time unit)

The precursor parameter V_{CE} is utilised to judge in which phase the IGBT stays, when the IGBT stays in the first degeneration phase, then:

$$S_f = \sum_{i=1}^{6} T_i \tag{5-2}$$

Where T_i is generated by Monte Carlo simulation and it means the duration time (time unit) of relevant phase. So the predicted RUL (RUL_p) could be represented as:

$$RUL_P = S_f - t = \sum_{i=1}^{6} T_i - t \tag{5-3}$$

When the IGBT stays in the ordinal of i degeneration phase, because the past generation phase is monitored by a sensor in the ageing experiment which could be reflected by the voltage of the V_{CE}. So S_{i-1} is a known number could be surveyed from the V_{CE} data recording. Then the predicted RUL could be calculated as:

$$RUL_{P_i} = S_f - t = \left(S_f - S_{i-1}\right) - (t - S_{i-1}) \tag{5-4}$$

Then

$$RUL_{P_i} = \sum_{i}^{6} T_i - (t - S_{i-1}) \tag{5-5}$$

Where if the simulated T_i generated by Monte Carlo simulation is larger than (t-S_{i-1}), it means that the IGBT is still and will continue in this degeneration phase, or the IGBT has ended the generation phase and begin to jump into the next degeneration phase.

In this model, Monte Carlo simulation is used to generate the duration time of each phase (T_i). In order to improve the accuracy of prediction, the Monte Carlo simulation is always simulated more than 500 times. The RUL prediction result uses the mean value of the distribution and the median value of the distribution.

5.2.3 Exponential Distribution

Exponential model is to use Exponential distribution to develop the prognostics algorithm to predict the IGBT RUL.

The whole IGBT process is separated into 6 degeneration phases and 6 stochastic models are built based on the 6 degeneration phases. The whole IGBT ageing process is modelled by 6 independent Exponential distribution models. Each model represents the relevant degeneration phase in the ageing process. As shown in figure 5-4, and the predicted RUL in Exponential model is also represented by equation 5-5

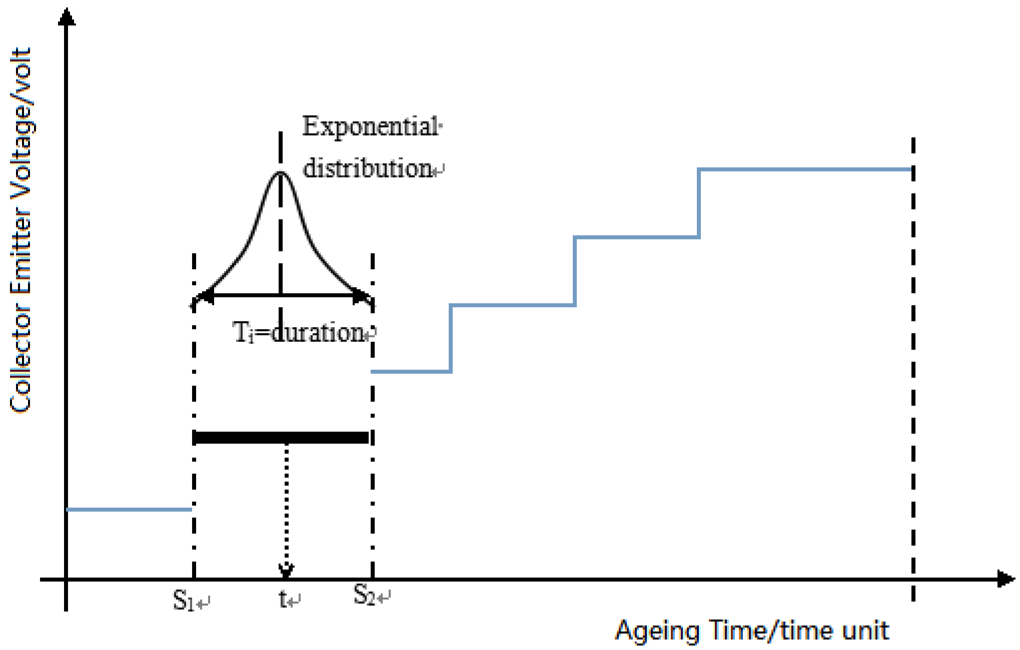

Figure 5-4 Exponential model to predict RUL

5.2.4 Poisson Distribution

Poisson model is to use Poisson distribution to develop the prognostics algorithm to predict the IGBT RUL.

The whole IGBT process is separated into 6 degeneration phases and 6 stochastic models are built based on the 6 degeneration phases. The whole IGBT ageing process is modelled by 6 independent Poisson distribution models. Each model represents the relevant degeneration phase in the ageing process. As shown in figure 5-5, and the predicted RUL in Poisson model is also represented by the equation 5-5

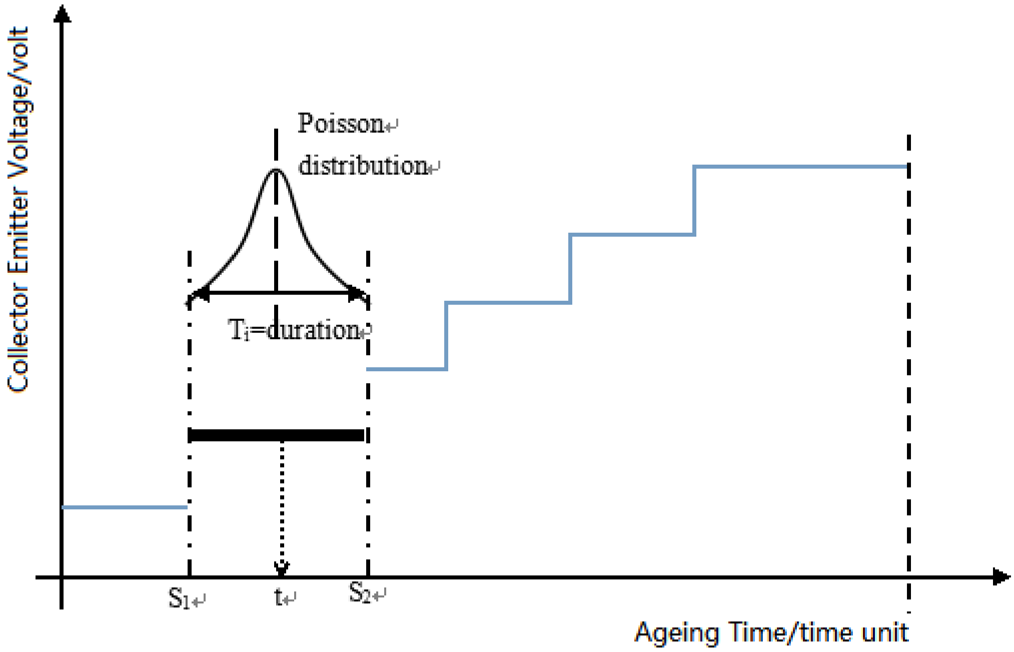

Figure 5-5 Poisson model to predict RUL

5.2.5 Combining Distribution

The combining model is based on the Gamma distribution, and two kinds of different models are built and combined to predict the IGBTs RUL.

As shown in figure 5-6, one kind of Gamma model is built and based on the duration time of the degeneration phase, and the other kind of Gamma model is built and based on the ending time of the degeneration phase.

The whole IGBT process is separated into 6 degeneration phases and 6 stochastic models are built based on the 6 degeneration phases, and one Gamma model is built which is based on the ending time of the degeneration phase. The distribution of these two kinds of probability models are combined to predict the IGBT RUL.

Monte Carlo simulation is based on the combining distribution of these two models to generate the random variable to predict the RUL.

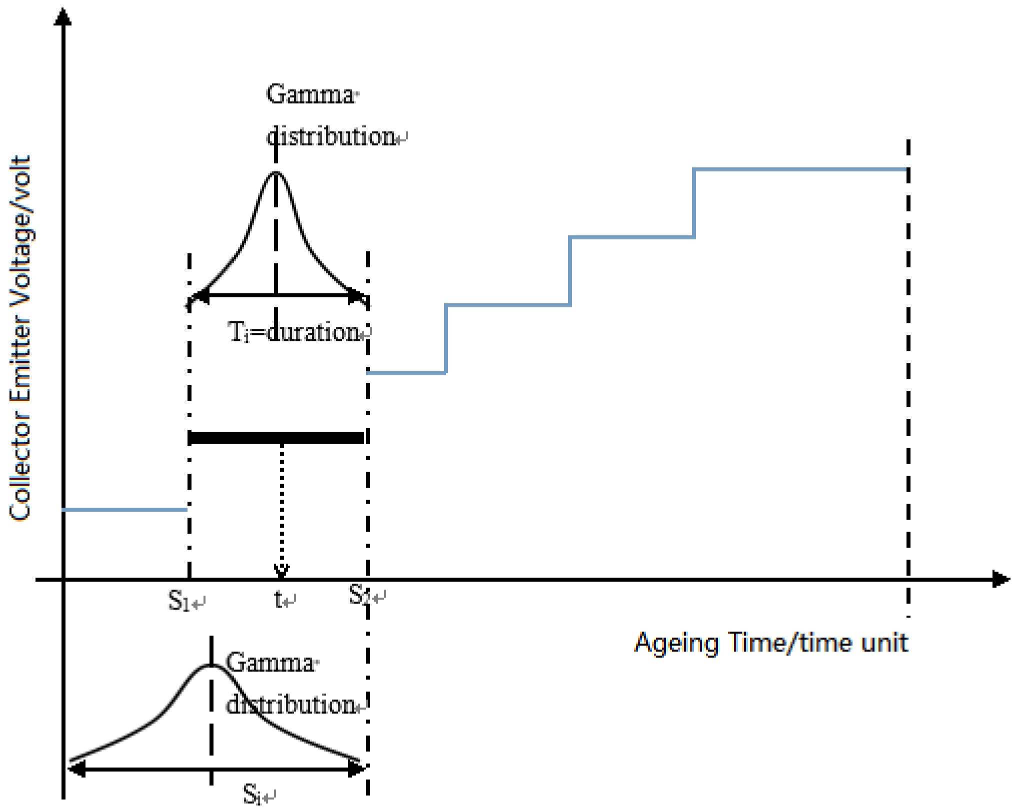

Figure 5-6 Combining model to predict RUL

When the IGBT stays in the ordinal of i degeneration phase, the ending time of the phase is S_i, and S_i could be represented as:

$$S_i = S_{i-1} + T_i \tag{5-6}$$

Where T_i is the time duration (time unit) of this degeneration phase which will be generated by Monte Carlo simulation, and S_{i-1} is the ending time (time unit) of the prior degeneration phase. So, S_{i-1} is a known number. T_i is simulated by Monte Carlo follow the model distribution which is based on the duration time of the degeneration phase.

According to the equation 5-6, the probability of S_i has the same distribution with T_i.

According to the model which is based on the ending time of the generation phase, the probability of S_i is different from the distribution of T_i, which means two probability distributions for S_i has been established. Combining these two distributions to predict the RUL is the main solution in this model.

5.3 Prediction Implementation of the Statistic Models

5.3.1 Prediction for IGBT No.1

Matlab was used in the implementation of the IGBT prognostics. The RUL prediction for IGBT No.1 implemented in Matlab is shown in figure 5-7. Four models were used in the prediction, and the results of the predicted mean RUL and the predicted median RUL were outputed. Each time the whole ageing process were carried out.

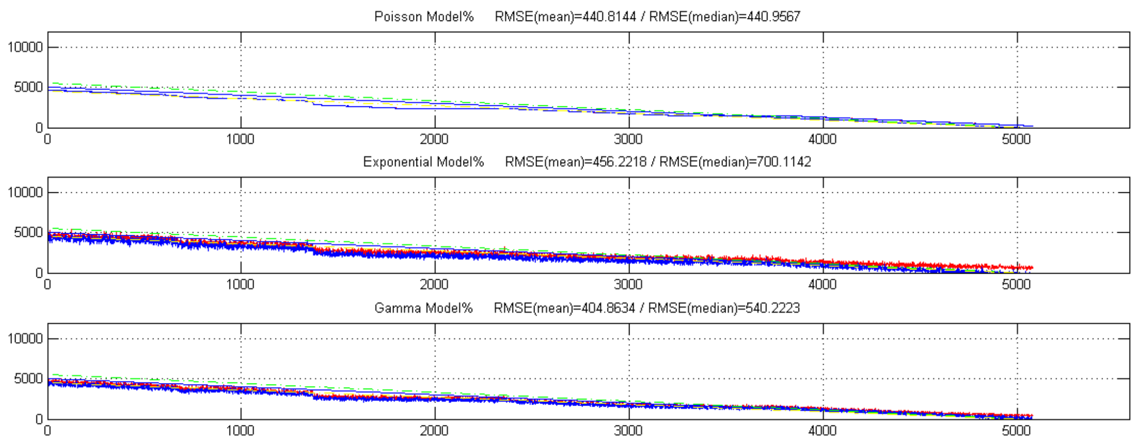

Figure 5-7 Prediction for IGBT No.1

Firstly, the IGBT ageing data are processed by the K-mean clustering method in Matlab, and the processed data are stored in an array named *training data*. Then, the ageing time and the duration time of each generation phase for seven IGBTs are computed and stored in the Matlab.

Secondly, the maximum likelihood estimate function is utilised to compute the Gamma, Exponential, Poisson distributions parameters.

Thirdly, the distribution parameters were input into the random function to generate random numbers as Gamma, Exponential and Poisson distributions, Trapezoidal numerical integration method and spline data interpolation method were used to generate random numbers following the combining distribution which combined the models explained in chapter 5.2.5. The random numbers are usually generated more than 500 times to increase the accuracy of the prediction.

Fourthly, the V_{CE} voltage value of each time unit is read by the Matlab and the data are used to distinguish the IGBT condition and degeneration phase.

Fifthly, RUL of IGBT is computed according to the different degeneration phases, and the results are outputed in Matlab as shown in figure 5-7.

5.3.2 Prediction for IGBT No.2

The RUL prediction for IGBT No.2 implemented in Matlab is shown in figure 5-8.

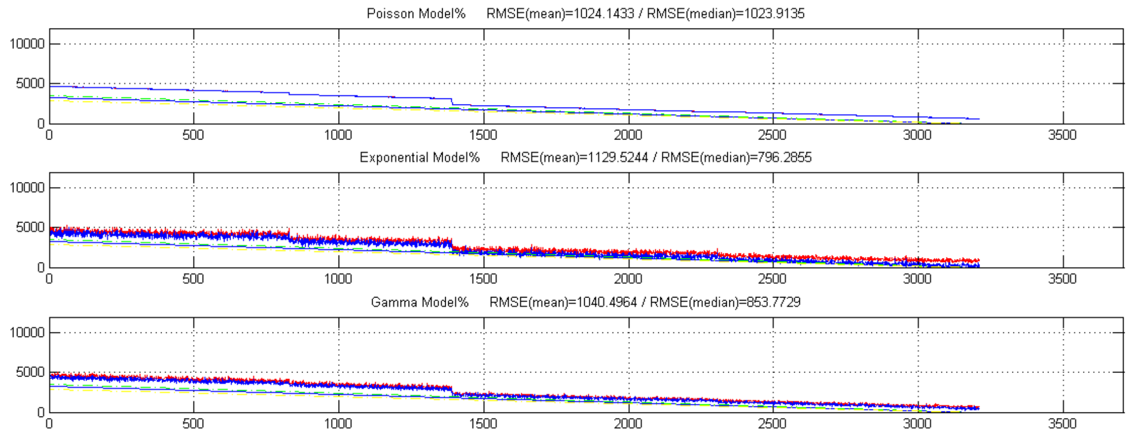

Figure 5-8 Prediction for IGBT No.2

5.3.3 Prediction for IGBT No.3

The RUL prediction for IGBT No.3 implemented in Matlab is shown in figure 5-9.

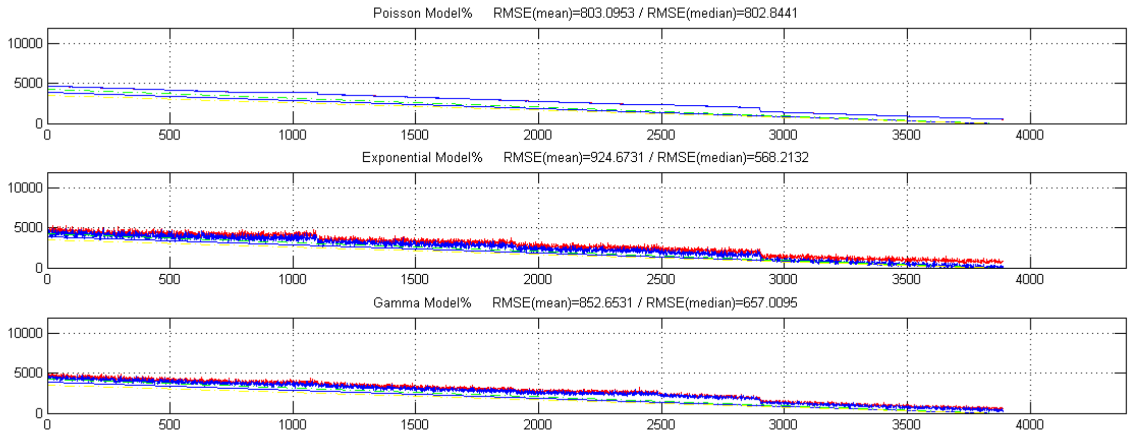

Figure 5-9 Prediction for IGBT No.3

5.3.4 Prediction for IGBT No.4

The RUL prediction for IGBT No.4 implemented in Matlab is shown in figure 5-10.

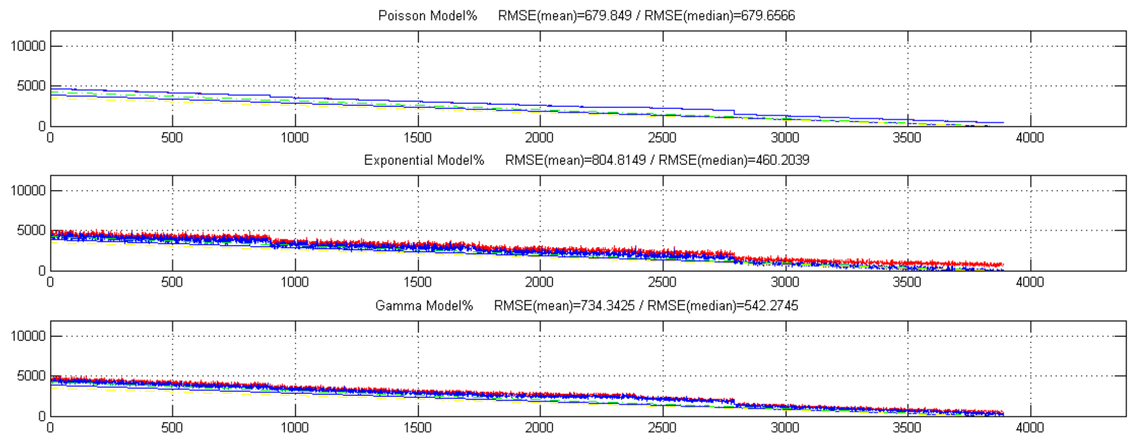

Figure 5-10 Prediction for IGBT No.4

5.3.5 Prediction for IGBT No.5

The RUL prediction for IGBT No.5 implemented in Matlab is shown in figure 5-11.

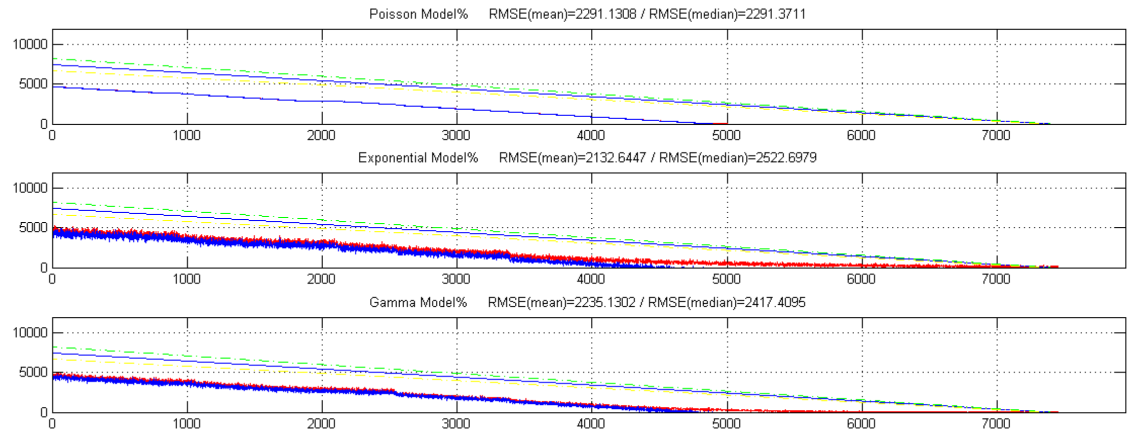

Figure 5-11 Prediction for IGBT No.5

5.3.6 Prediction for IGBT No.6

The RUL prediction for IGBT No.6 implemented in Matlab is shown in figure 5-12.

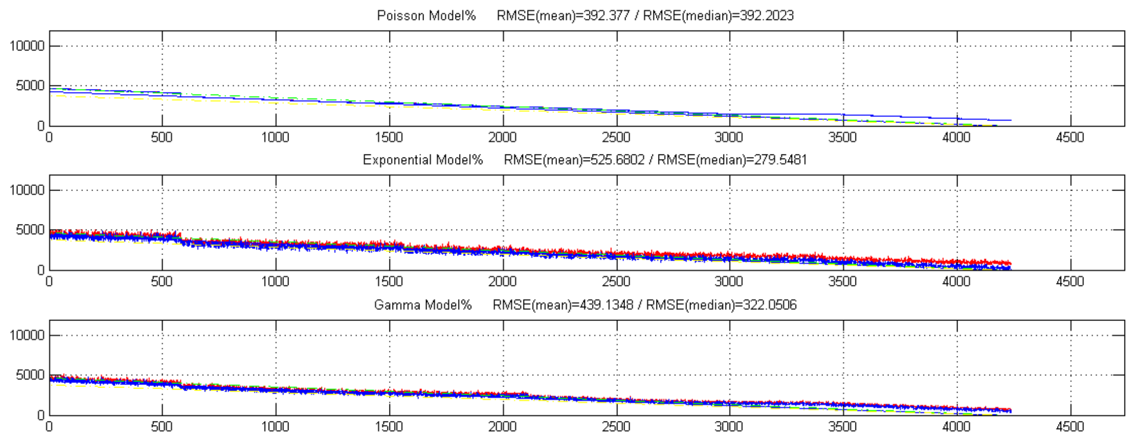

Figure 5-12 Prediction for IGBT No.6

5.3.7 Prediction for IGBT No.7

The RUL prediction for IGBT No.7 implemented in Matlab is shown in figure 5-13.

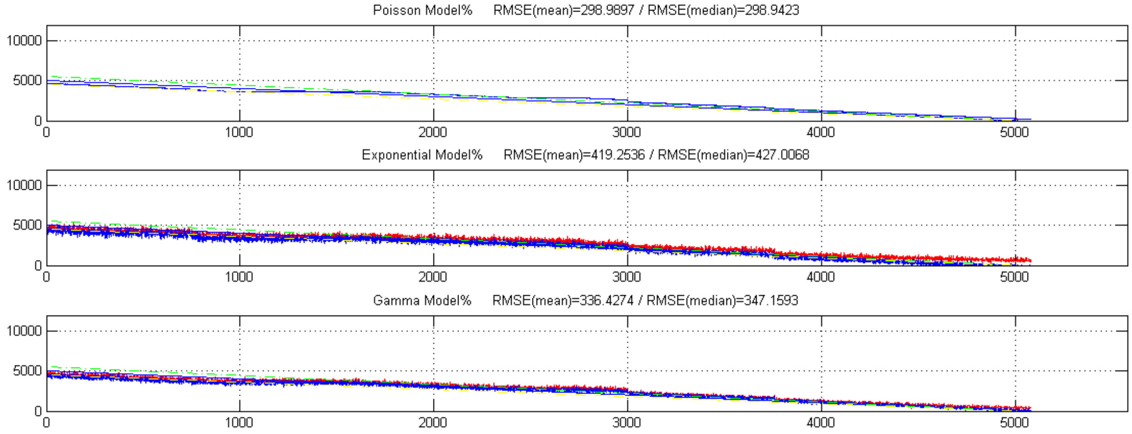

Figure 5-13 Prediction for IGBT No.7

5.4 Prognostics Algorithm

IGBT prognostics algorithm is the computing method and procedure used to predict the IGBT RUL and control the implementation process of the computing and prediction. It also includes the framework for prognostics of IGBT. In this study, the IGBT prognostics algorithm is developed in Matlab.

As shown in figure 5-14, the algorithm consists of 5 main steps:

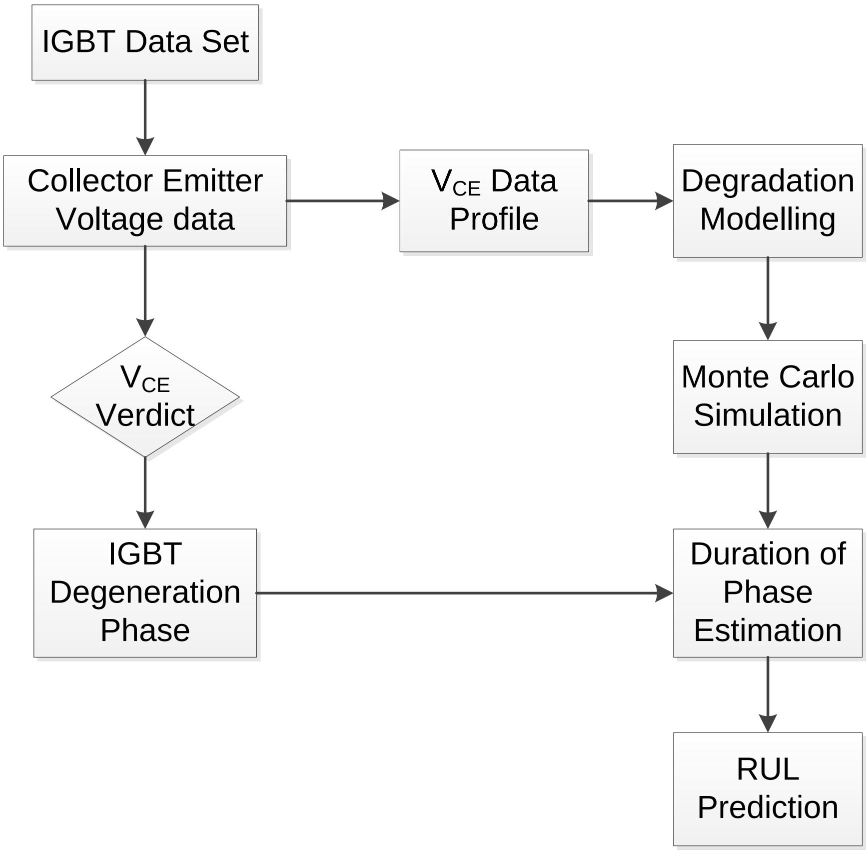

Figure 5-14 IGBT RUL prediction algorithm flow chart

The first step is data processing, which includes three sub-steps. Firstly, the K-mean clustering method is used to process the original V_{CE} data. Secondly, the IGBT ageing process is separated into 6 stages according to the feature of the V_{CE} data. Thirdly, the time duration of each stage is computed according to the V_{CE} value, and the results of data processing will be the foundation and samples of the modelling and RUL prediction.

The second step is modelling. The main task of modelling is to determine the parameters of the models. The maximum likelihood function in Matlab is used to compute the models parameters and the processed data from step 1 are used as input for calculating the models parameters. Loop control statement is used here to acquire the Gamma models parameters, Exponential models parameters and Poisson models parameters at the same time.

The third step is to use Monte Carlo method to simulate the IGBT degeneration phenomena. This step consists of 2 sub-steps. Firstly, the random number function is used to generate random numbers following the probability distribution of the models, and then the voltage of the V_{CE} is used to compare with the standard value of the V_{CE} in each degeneration phase to judge the IGBT condition.

The fourth step is RUL prediction, which is carried out according to the equation 5-5, random numbers generated by Monte Carlo simulation and the condition of the IGBT in which degeneration phase is the input, and the output includes the predicted mean RUL, predicted median RUL and the confidence interval.

The fifth step is results outputting, Matlab is used to output the prediction result in figures, tables and charts.

The Matlab code and procedures used to predict the IGBT RUL is attached in Appendix.

6 Results Analysis

6.1 Prediction Results

The IGBT RUL prediction results are expressed by a series of polylines. The RUL prediction is a continuous process from the beginning of the IGBT running to the end of the process when IGBT is failing. The sensor data are recorded at each moment of the IGBT degradation process and the RUL prediction are also carried out at each moment of the degradation process. Hence, the RUL prediction happens through the whole process of the IGBT degradation experiment.

As shown in figure 6-1, it indicates the RUL prediction results for the IGBT-No.1 computing using Gamma model, which was computed in Matlab.

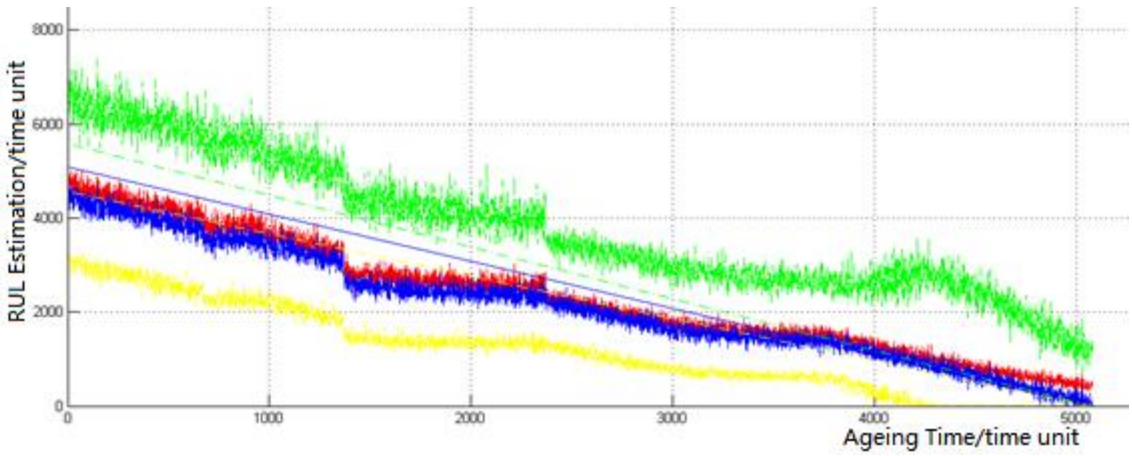

Figure 6-1 RUL Prediction Result in Gamma Model

The blue line in figure 6-1 represents the real remaining useful life of IGTB-No.1, and the green dash line and the yellow dash line represent the ±10% error range from the real RUL value. The red vibrating polyline in the figure shows the average value of the RUL prediction in Gamma distribution and the blue vibrating polyline represents the median value of the RUL prediction. The green vibrating polyline in the topside of the figure is the confidence upper limit of the Gamma distribution in 90% and the yellow polyline in the bottom is the 10% confidence limit of the Gamma distribution.

The figure shows that the IGBT-No.1 RUL prediction results (the mean RUL prediction value and the median RUL prediction value) in the beginning of the ageing experiment is a little lower than the real RUL value, but the real RUL value is in the confidence interval of the RUL prediction value.

As shown in figure 6-2, it indicates the RUL prediction results for the IGBT-No.1 computing using Exponential model, which was computed in Matlab.

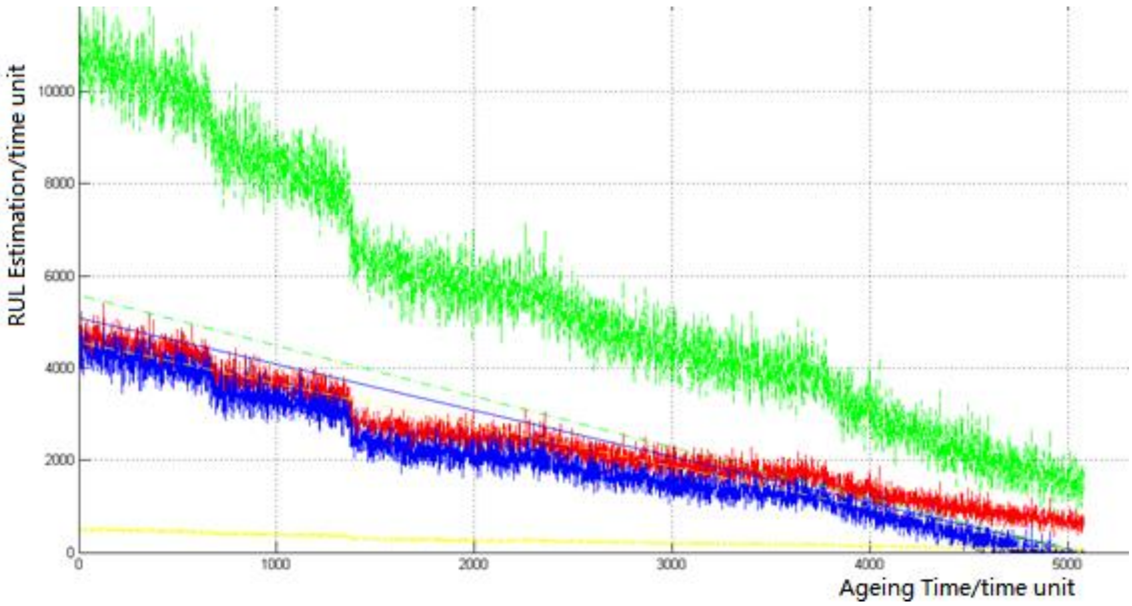

Figure 6-2 RUL Prediction Result in Exponential Model

The blue line in figure 6-2 represents the real remaining useful life of IGTB-No.1, and the green dash line and the yellow dash line represent the ±10% error range from the real RUL value. The red vibrating polyline in the figure shows the average value of the RUL prediction in Exponential distribution and the blue vibrating polyline represents the median value of the RUL prediction. The green vibrating polyline in the topside of the figure is the confidence upper limit of the Exponential distribution in 90% and the yellow polyline in the bottom is the 10% confidence limit of the Exponential distribution.

As shown in figure 6-3, it indicates the RUL prediction results for the IGBT-No.1 computing using Poisson model, which was computed in Matlab.

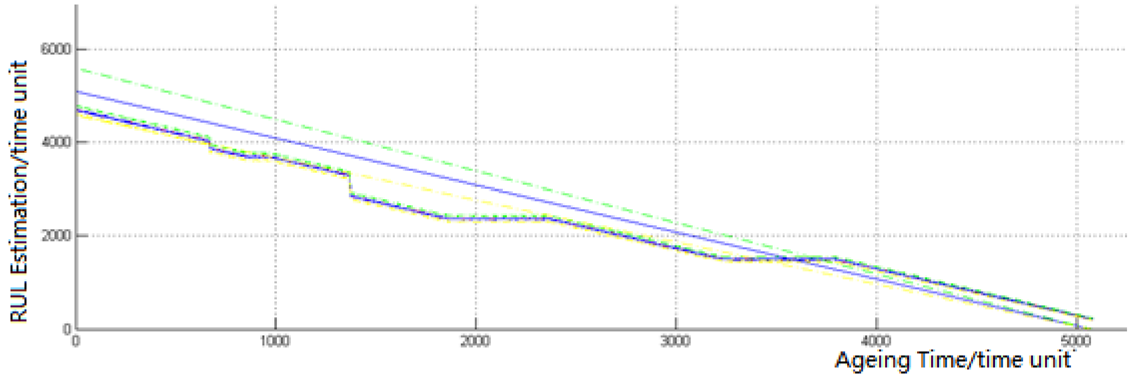

Figure 6-3 RUL Prediction Result in Poisson Model

The blue line in figure 6-3 represents the real remaining useful life of IGTB-No.1, and the green dash line and the yellow dash line represent the ±10% error range from the real RUL value. The red vibrating polyline in the figure shows the average value of the RUL prediction in Poisson distribution and the blue vibrating polyline represents the median value of the RUL prediction. The green vibrating polyline in the topside of the figure is the confidence upper limit of the Poisson distribution in 90% and the yellow polyline in the bottom is the 10% confidence limit of the Poisson distribution.

Figure 6-4 indicates the IGBT-No.1 RUL prediction results using combining model, the combining model is based on the gamma distribution.

The blue line in figure 6-4 represents the real remaining useful life of IGTB-No.1, The red vibrating polyline in the figure shows the average value of the RUL prediction and the blue vibrating polyline represents the median value. The green vibrating polyline in the topside of the figure is the confidence upper limit and the yellow polyline in the bottom is the 10% confidence limit of the model.

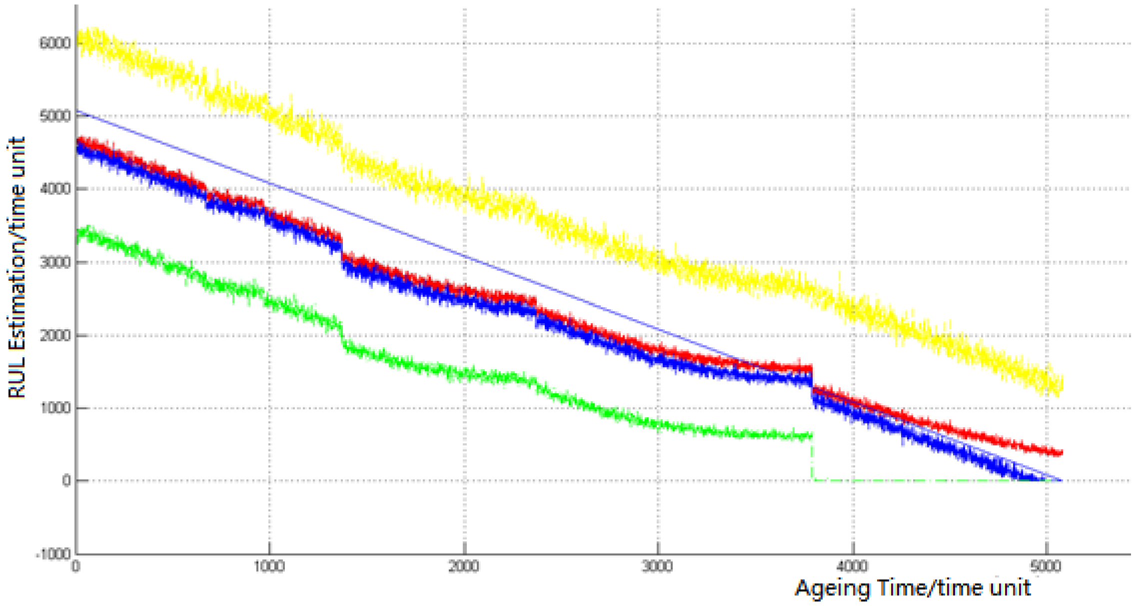

Figure 6-4 RUL Prediction Result in Combining Model

The results of the RUL prediction for other 6 IGBTs (No.2 ~ No.7) are listed in Appendix

6.2 Accuracy Analysis

The errors between the RUL prediction value and the real RUL value reflect the accuracy of the IGBT prognostics approach. Different models have different error values and table 6-2 indicates the predicting error of different models in the selected time for IGBT No.1 during the whole RUL prediction process.

The error between the RUL prediction value and the real value could be represented by equation 6-1

$$E_r = RUL_R - RUL_P \tag{6-1}$$

Where E_r means the error value between the prediction value and the real value, and RUL_R is the real value of the IGBT remaining useful life, which is the IGBT life (running-to-fail time) minus the IGBT service time in the ageing experiment. The RUL_P is the prediction value from the prognostics algorithm described in chapter 5.

In the table 6-1, the RUL prediction values at the ageing time (time unit) of 0, 1000, 2000, 3000, 4000, and the fail time of the IGBT (5079) are indicated, and table 6-2 indicates the error values of the RUL prediction at these moments.

As shown in table 6-1, at the beginning of the IGBT degradation process the real RUL (the IGBT life) is higher than the prediction value in all three models, and the RUL prediction error computed from the Poisson model is much less than the other models which could be found from table 6-2. At the end of the IGBT degradation process the all three RUL predictions from different models are greater than zero, and the error value from the Poisson model approximates much better than others again. However, at the time unit of 2000, the Poisson model has the biggest error value (713).

Table 6-1 RUL prediction results

Time(time unit)	0	1000	2000	3000	4000	5079
Gamma (time unit)	4554	3466	2590	1894	1227	527
Exponential (time unit)	4489	3399	2636	1712	1342	764
Poisson (time unit)	4695	3655	2367	1734	1294	216

time unit: represents time durations at a given unit in the experiments

Table 6-2 The RUL prediction errors

Time(time unit)	0	1000	2000	3000	4000	5079
Gamma (time unit)	525	614	490	186	-147	-527
Exponential (time unit)	590	681	444	368	-262	-764
Poisson (time unit)	384	425	713	346	-214	-216

time unit: represents time durations at a given unit in the experiments

Figure 6-5 shows the error value of the real RUL in comparison with the predicted RUL computed by the Gamma model from the beginning of the IGBT degradation experiment until the IGBT fails.

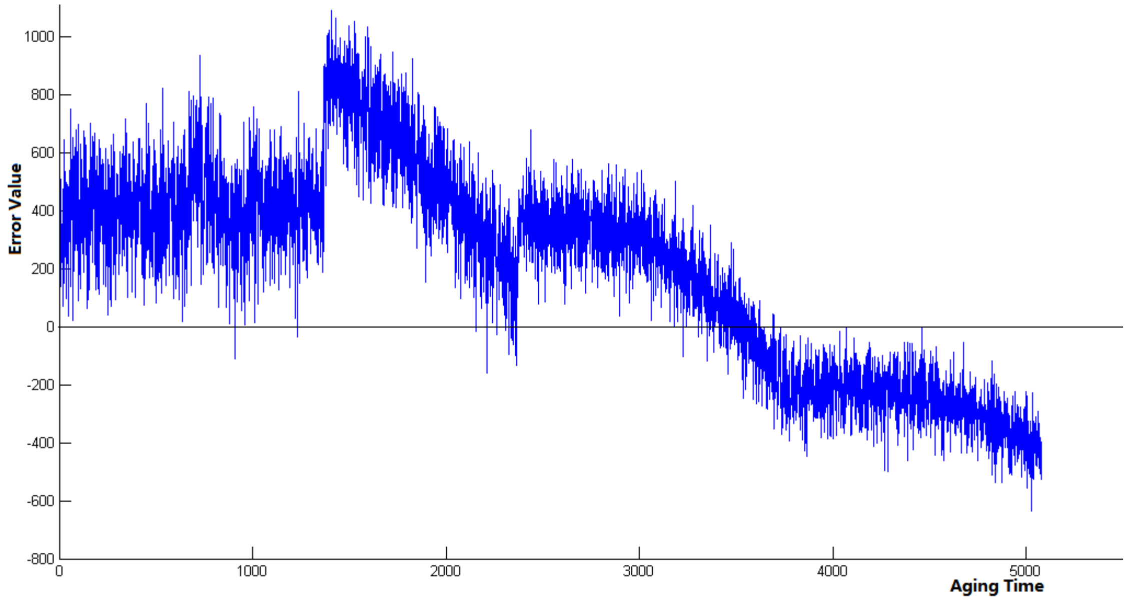

Figure 6-5 Errors computed by Gamma model

Figure 6-6 shows the error value between the real RUL and the predicted RUL computed by the Exponential model from the beginning of the IGBT degradation experiment until the IGBT fails.

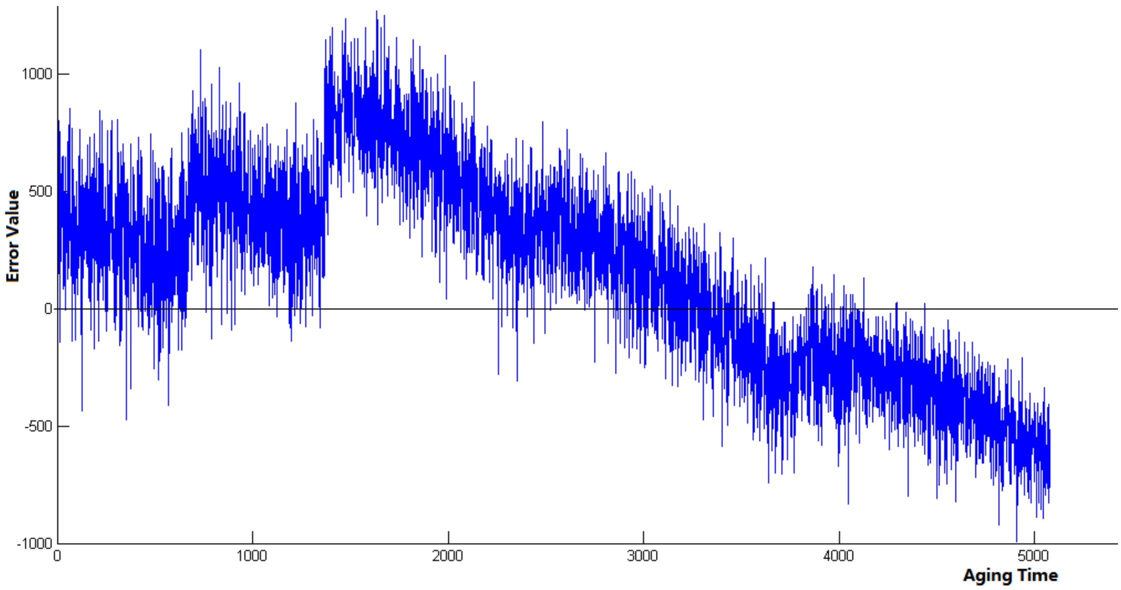

Figure 6-6 Errors computed by Exponential model

Figure 6-7 shows the error value between the real RUL and the predicted RUL computed by the Poisson model from the beginning of the IGBT degradation experiment until the IGBT fails.

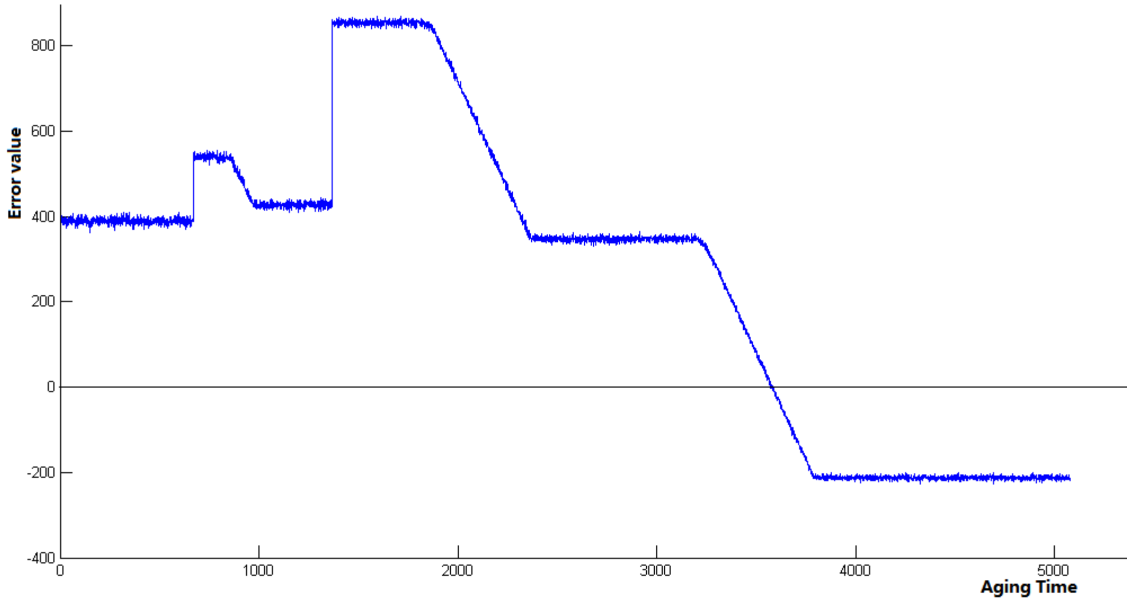

Figure 6-7 Errors computed by Poisson model

The trends of the errors for the three models in predicting the RUL of IGBT No.1 in the whole ageing process show a similar dynamic change. The errors of three models increase slightly from 0 to 1500 (time unit), and then the errors all decrease to 0 nearly at 3500 (time unit), but after that, there are an increase in the opposite direction for the errors.

The accuracy of the RUL prediction could use equation 6-2 to compare

$$P_{pr} = \frac{E_r}{RUL_R} = \frac{RUL_R - RUL_P}{RUL_R} \qquad \textbf{(6-2)}$$

Where P_{pr} is the accuracy of the RUL prediction

E_r is the error value between the real RUL and the predicted RUL

RUL_R is the real remaining useful life of the IGBTs

RUL_P is the predicted RUL value

After computing in Matlab, the accuracy of the whole ageing process for IGBT No.1 is indicated in figure 6-8, the accuracy of the RUL prediction almost stay constant at 0 before the 5000 (time unit) when the IGBT begin to fail. For all three models the profile of the accuracy for RUL prediction is almost the same before the IGBT begins to fail.

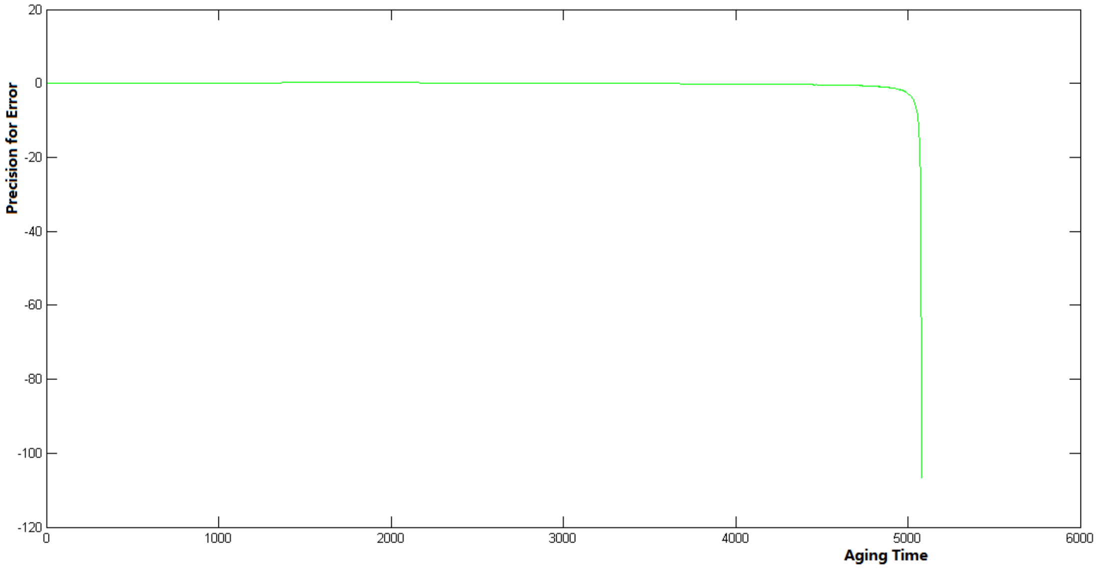

Figure 6-8 Precision of the predicted RUL in the whole process

6.3 Root Mean Square Error Comparing

Root mean square error (RMSE) is used to compare the efficiency and measures the difference of different models in predicting the IGBT RUL. The calculation formula of the mean root mean square error is:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(\widehat{Y_i} - Y_i\right)^2 \tag{6-3}$$

$$\mathrm{MSE} = \frac{1}{T_f}\sum_{i=1}^{T_f}\left(RUL_{P_i} - RUL_{R_i}\right)^2 = \frac{1}{T_f}\sum_{i=1}^{T_f}(Er_i)^2 \tag{6-4}$$

$$\mathrm{RMS} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\widehat{Y_i} - Y_i\right)^2} = \sqrt{\frac{1}{T_f}\sum_{i=1}^{T_f}(Er_i)^2} \tag{6-5}$$

Where T_f is the life time of the IGBT in the accelerated ageing experiment (time unit)

E_r is the error value between the real RUL and the predicted RUL (time unit)

According to the equation 6-5, and the RMSEs of each model in predicting the IGBTs RUL are listed in table 6-3 and table 6-4 after computing in Matlab. The former is the RMSEs for mean values of RUL prediction and the latter is the RMSEs for median values. Seven IGBTs RULs are predicted in three models with the results of mean predicted RULs and median predicted RULs.

Table 6-3 RMSEs for the mean value of predicted RUL

	No.1	No.2	No.3	No.4	No.5	No.6	No.7
Gamma	403.1	1040.3	854	736.4	2235	440.9	338.5
Exponential	455.8	1129.3	925.1	804.8	2132.4	525.8	419.2
Poisson	440.8	1024.1	803.1	679.8	2291.1	392.4	299
Combinning	351	1239.5	845.8	771.4	2245.3	458.7	250.9

Table 6-4 RMSEs for the median value of predicted RUL

	No.1	No.2	No.3	No.4	No.5	No.6	No.7
Gamma	549	843.9	646	533.2	2423.9	322.9	354.4
Exponential	699.2	794.7	569.9	460.5	2523.2	278.9	428.3
Poisson	440.9	1024	802.9	679.7	2291.4	392.2	298.9
Combinning	441.7	1106.6	713.4	634.7	2397	326.8	272.1

Figure 6-9 and figure 6-10 compare the RMSEs in different models for different IGBTs. As shown in the figures, the Poisson model performs much better than other models for IGBT No.2, No.3, No.4 and No.6. Because the RMSEs of mean predicted RULs are less than other models. However, the exponential models of these IGBT have less value of RMSEs for their median predicted RULs than other models.

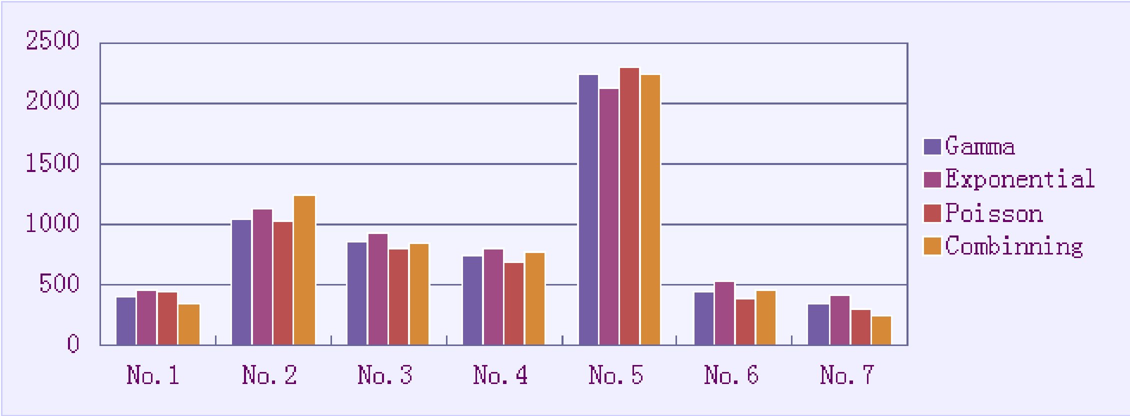

Figure 6-9 RMSE for the mean value of predicted RUL in different models

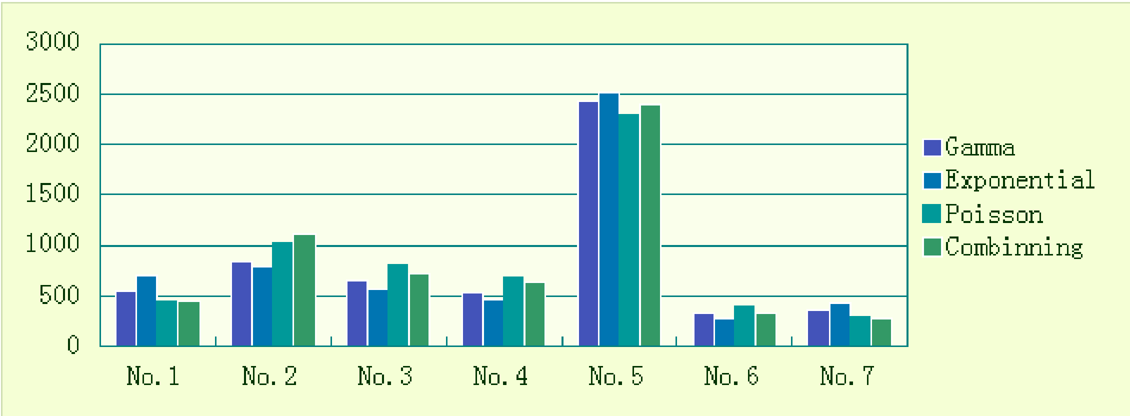

Figure 6-10 RMSE for the median value of predicted RUL in different models

The dynamic changes of the RMSE of mean and median predicted RULs in the whole IGBT ageing process are presented from figure 6-10 to figure 6-16 for different models.

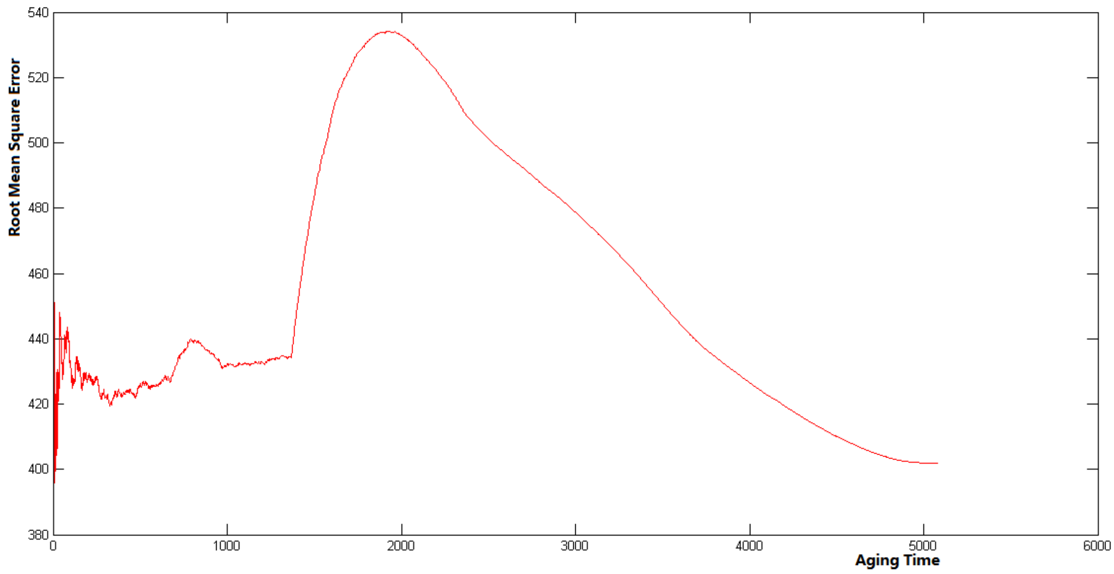

Figure 6-11 RMSE of mean RUL value in Gamma model

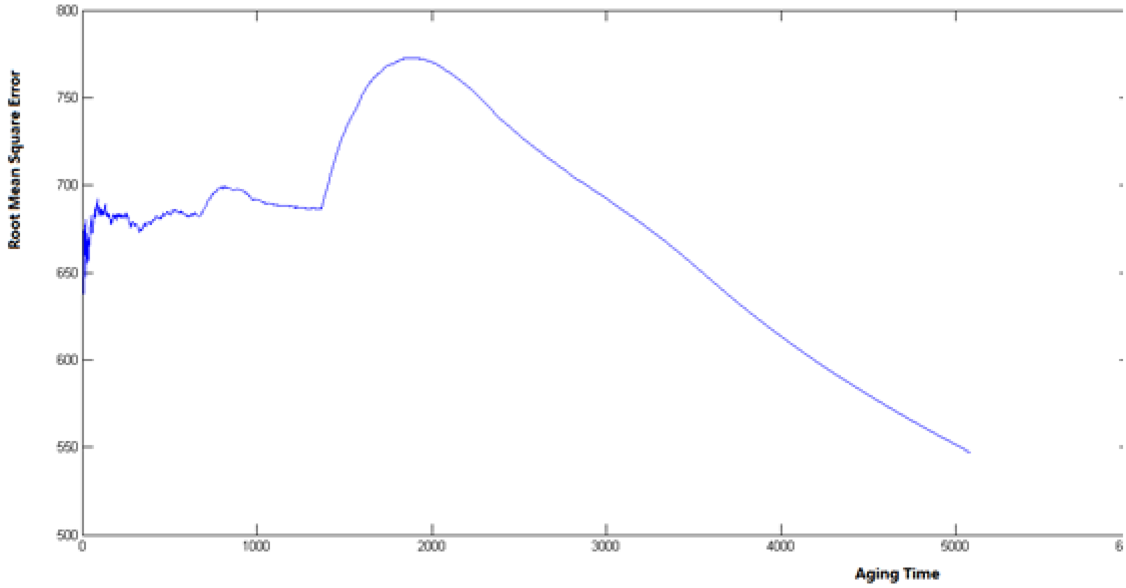

Figure 6-12 RMSE of median RUL value in Gamma model

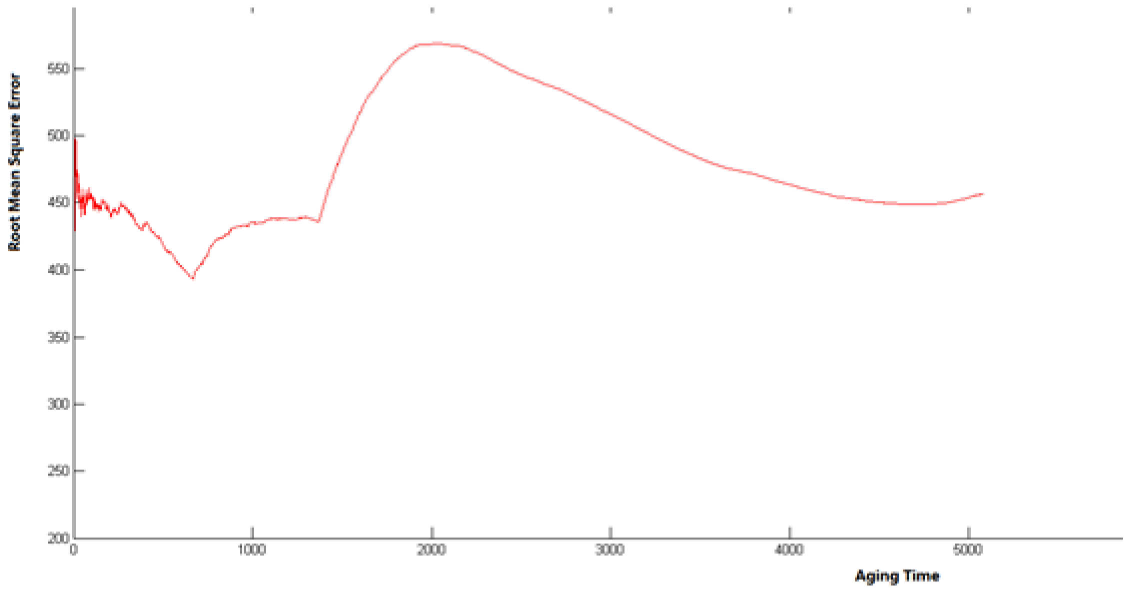

Figure 6-13 RMSE of mean RUL value in Exponential model

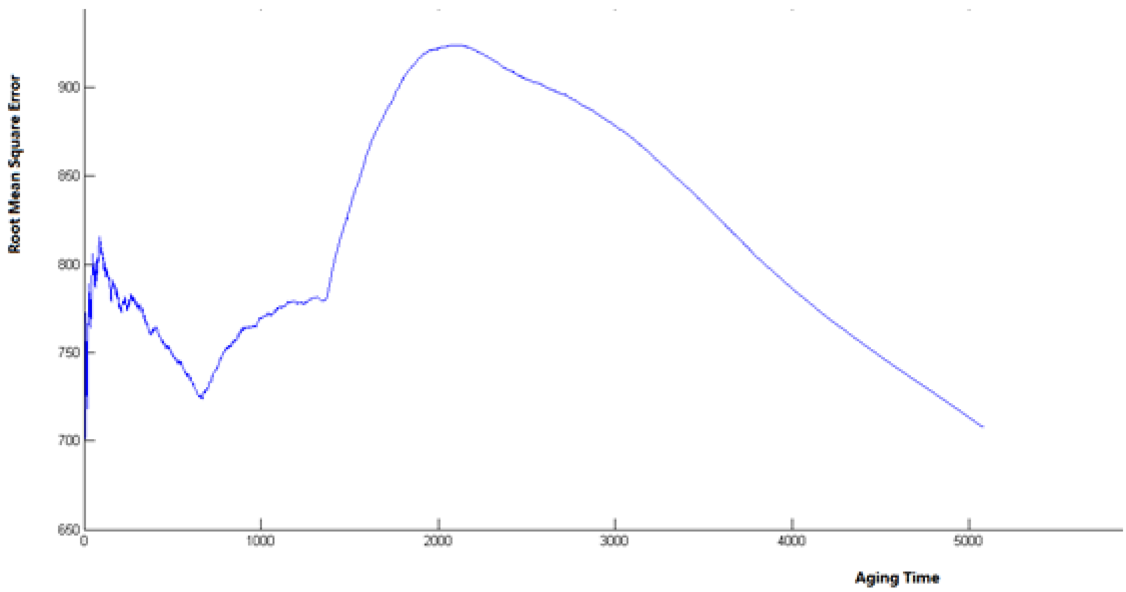

Figure 6-14 RMSE of median RUL value in Exponential model

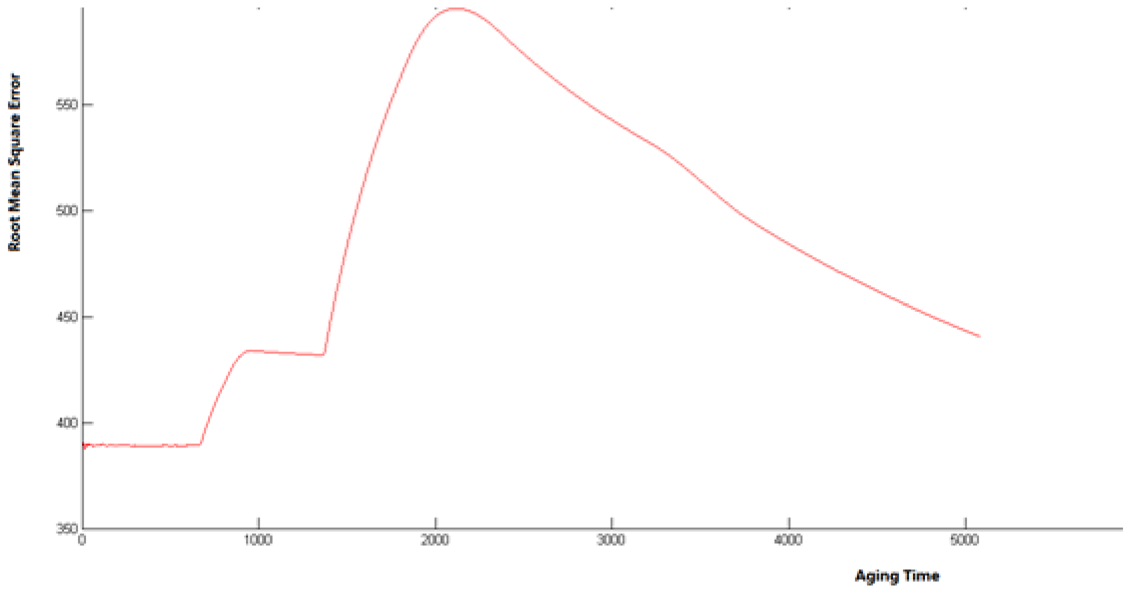

Figure 6-15 RMSE of mean RUL value in Poisson model

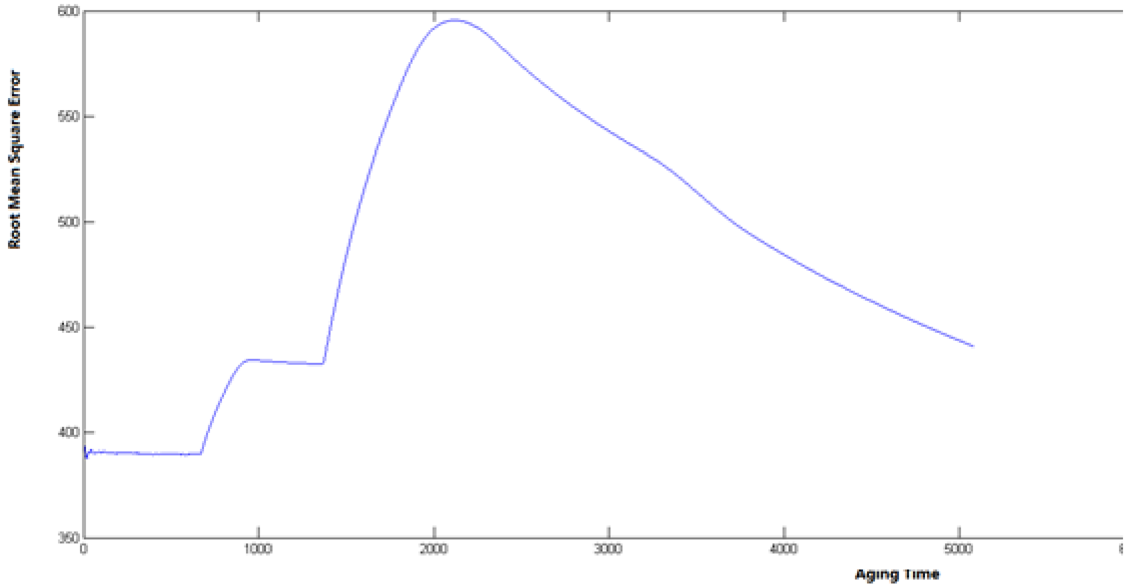

Figure 6-16 RMSE of median RUL value in Poisson model

6.4 Benefits and Challenges of Different Stochastic Model

According to the analysis, it is clear to found that different models and different predicted RULs have different RMSEs, and it illustrates that each model has its benefits and challenges on the predicting of each IGBT.

Comparing the RMSE of mean predicted RUL and the median predicted RUL, The No.1 and No.7 IGBTs both have the smallest RMSE for combining model with mean predicted RUL, and the Exponential model with median predicted RUL has the largest RMSE. However, the No.2 IGBT has an exactly opposite performance, the RMSE of the Exponential model with median predicted RUL is much less than other models and the combining model with mean predicted RUL is the biggest one of all RMSEs for No.2.

The rest of other IGBT, No.3, No.4, No.5 and No.6, have the same situation in RUL prediction, the Exponential model with median predicted RUL has the smallest RMSE, but the Exponential model with mean predicted RUL has the largest RMSE.

In constrict with Exponential model, Poisson model almost has the same RMSE between its mean predicted RUL and median predicted RUL.

7 Conclusions and Further Work

7.1 Conclusions

The main contribution of this study is the development and implementation of a prognostics framework for IGBTs, and a prognostics algorithm with Monte Carlo simulation and with the collector emitter voltage as a precursor parameter.

According to the IGBT failure mechanism and degradation characterization, the IGBT degeneration models are built. Monte Carlo simulation method and the precursor parameter, collector emitter voltage (V_{CE}), are integrated to develop the prognostics algorithm on predicting the IGBT remaining useful life (RUL)

Gamma, Exponential and Poisson distribution models and the combining distribution model are used, and Monte Carlo simulation is utilised in the algorithm to computing the IGBT remaining useful life. The collector emitter voltage (V_{CE}) is used as precursor parameter in prognosis to predict the RUL. Seven IGBTs were studied in this prognostics research.

Comparing with the results of RUL prediction with different models, the mean value of the RUL prediction and the median value of the RUL prediction presents a different accuracy. Different models also perform their preference to different IGBTs on the RUL prediction.

The implementation of the developed prognostics framework can help provide advance warning of failures thereby preventing costly IGBT failures and system downtime.

7.2 Future Work

Further research is needed to implement the developed prognostics approach in a real world application.

The results of RUL prediction with different models are compared in this thesis, and the V_{CE} is the precursor parameters in the IGBT prognostics. A comparative analysis between the results of RUL prediction based on different precursor parameters could be implemented in the future research.

The combining model performs a much more efficient RUL prediction results in some IGBTs, and the combining model in this thesis is only based on the Gamma distribution, much more combining models based on different probability distribution could be established and implemented in IGBTs RUL prediction, and a comparative analysis between these combining models is beneficial to the IGBT prognostics.

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APPENDICES

Appendix A Prognostics codes

The Matlab procedure codes used to predict the RUL of IGBT and computing the Root mean square errors are below:

```
clc

clear all

K = [ 670, 970, 1368, 2369, 3793, 5079, 10740;

      827, 827, 1389, 1389, 2306, 3208, 5075;

      1099, 1099, 1905, 2490, 2900, 3889, 6799;

      894, 894, 1733, 2384 2789, 3887, 5141;

      927, 1055, 2115, 2544, 3388, 7449, 10285;

      578, 578, 1560, 2109, 3403, 4236, 12164;

      750, 1631, 2755, 3001, 3757, 5079, 6861 ];


dats=zeros(7,6);

dats(:,1)=K(:,1);

for j=2:6

   dats(:,j)=K(:,j)-K(:,j-1);

end

dats=[dats,K(:,6)]

Z=zeros(7,1);

K=[Z,K];
```

```
for i=1:42
    if dats(i)==0
        dats(i)=0.00001;
    end
end

%Distribution Modelling
mod=['Poisson Model    ';'Exponential Model';'Gamma Model      ';'Weibull Model    '];
for j=1:6
    [phat, pci] = poissfit(dats(:,j));
    p(j)=phat;
    [phat, pci] = expfit(dats(:,j));
    l(j)=phat;
    [phat, pci] = gamfit(dats(:,j));
    a(j)=phat(1);
    b(j)=phat(2);
    [phat, pci] = wblfit(dats(:,j));
    g(j)=phat(1);
    h(j)=phat(2);
end

% RUL Estimation
```

```
pic=1;
for j=1:7

    mp=100;
    t=0;
    n=1;

    rul=[];
    mrul=[];
    maxrul=[];
    minrul=[];
    ee=[];
    mee=[];

    while t<(K(j,7)+1)

        while t<(K(j,n+1)+1)
            dur=zeros(4,6);
            sul=zeros(4,mp);

            for m=1:mp    %Montel Calo Simulation mp times
                for i=n:6
                    dur(1,i)=poissrnd(p(i));
```

```
        dur(2,i)=exprnd(l(i));
        dur(3,i)=gamrnd(a(i),b(i));
        dur(4,i)=wblrnd(g(i),h(i));
    end
    for i=1:4
        if dur(i,n)<t-K(j,n)
            sul(i,m)=sum(dur(i,:))-dur(i,n);
            if sul(i,m)==0
                sul(i,m)=0.00001;
            end
        else
            sul(i,m)=sum(dur(i,:))-(t-K(j,n));
            if sul(i,m)==0
                sul(i,m)=0.00001;
            end
        end
    end
end
t=t+1;

for i=1:4
    rul(i,t)=mean(sul(i,:));
    mrul(i,t)=median(sul(i,:));
```

```
    switch i
        case 1
            [phat, pci] = poissfit(sul(i,:));
            maxrul(i,t)=poissinv(0.9, phat);
            minrul(i,t)=poissinv(0.1, phat);
        case 2
            [phat, pci] = expfit(sul(i,:));
            maxrul(i,t)=expinv(0.9, phat);
            minrul(i,t)=expinv(0.1, phat);
        case 3
            [phat, pci] = gamfit(sul(i,:));
            maxrul(i,t)=gaminv(0.9, phat(1),phat(2));
            minrul(i,t)=gaminv(0.1, phat(1),phat(2));
        case 4
            [phat, pci] = wblfit(sul(i,:));
            maxrul(i,t)=wblinv(0.9, phat(1),phat(2));
            minrul(i,t)=wblinv(0.1, phat(1),phat(2));
    end

    %RMSE error
    ee(i,t)=(dats(j,7)-t-rul(i,t)+1)^2;
    mee(i,t)=(dats(j,7)-t-mrul(i,t)+1)^2;
end
```

```
    end

    n=n+1;

end

for i=1:4
    RMSE(i,j)=sqrt(sum(ee(i,:))/t);
    MRMSE(i,j)=sqrt(sum(mee(i,:))/t);
end

%figure(j)
for i=1:4
    %subplot(4,1,i)

    figure(pic)
    plot(rul(i,:),'r-')
    xlim([0,dats(j,7)+500])
    ylim([0,12000])
    grid on
    hold on
    plot(mrul(i,:),'b-')
    plot(maxrul(i,:),'g-.')
```

```
        plot(minrul(i,:),'y-.')

        plot([dats(j,7),0],[0,dats(j,7)])

        plot([dats(j,7),0],[0,dats(j,7)*1.1],'g-.')

        plot([dats(j,7),0],[0,dats(j,7)*0.9],'y-.')

        title(strcat(mod(i,:),'%                    RMSE(mean)=',num2str(RMSE(i,j)),'    /
RMSE(median)=',num2str(MRMSE(i,j))))

        hold off


        pic=pic+1;


    end


end


MSE=[RMSE;MRMSE]
```

Appendix B Prognostics results

The results of the RUL prediction for the IGBTs (No.2 ~ No.7) are below:

IGBT No.2 RUL prediction results

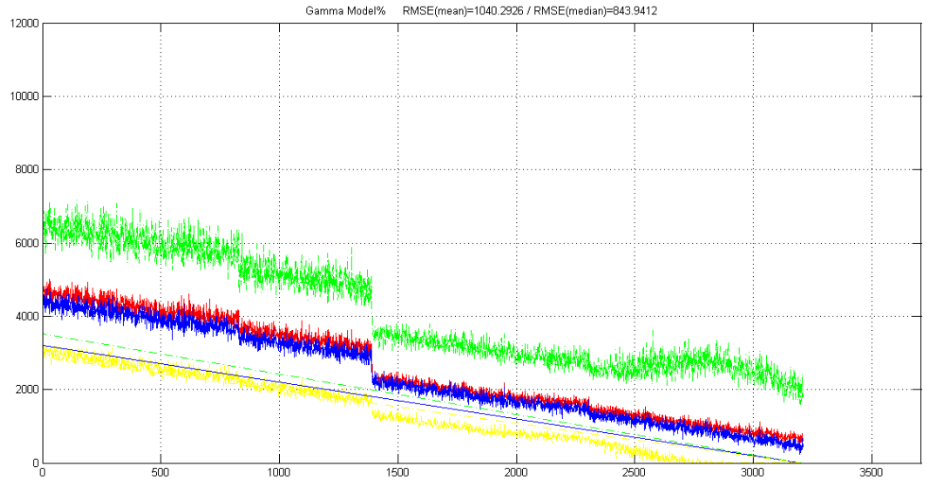

Figure B-1 RUL Prediction result of IGBT No.2 with Gamma model

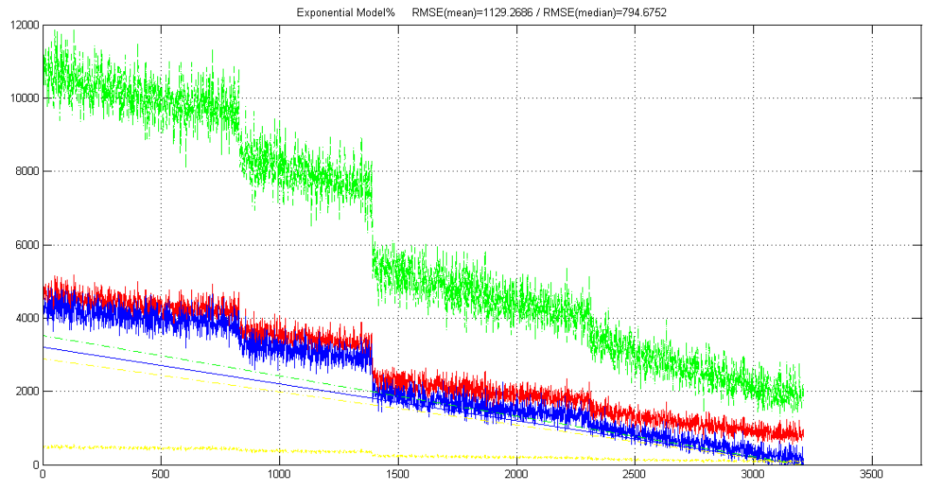

Figure B-2 RUL Prediction result of IGBT No.2 with Exponential model

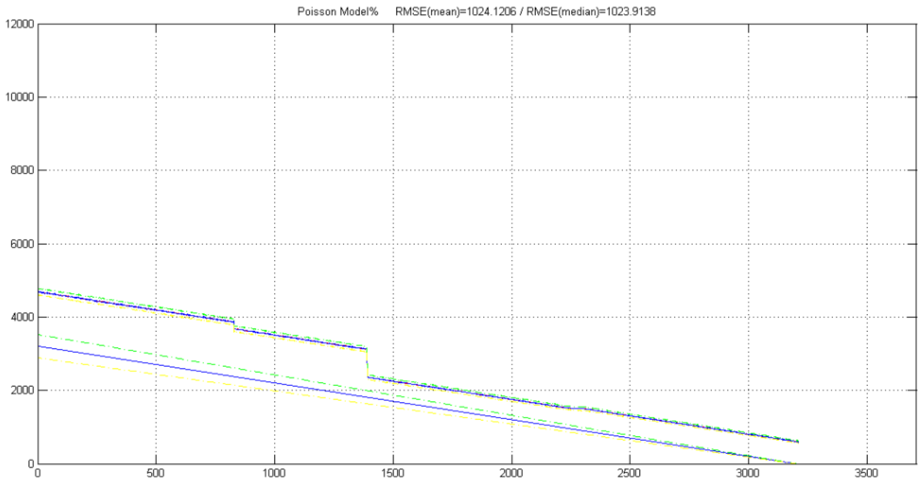

Figure B-3 RUL Prediction result of IGBT No.2 with Poisson model

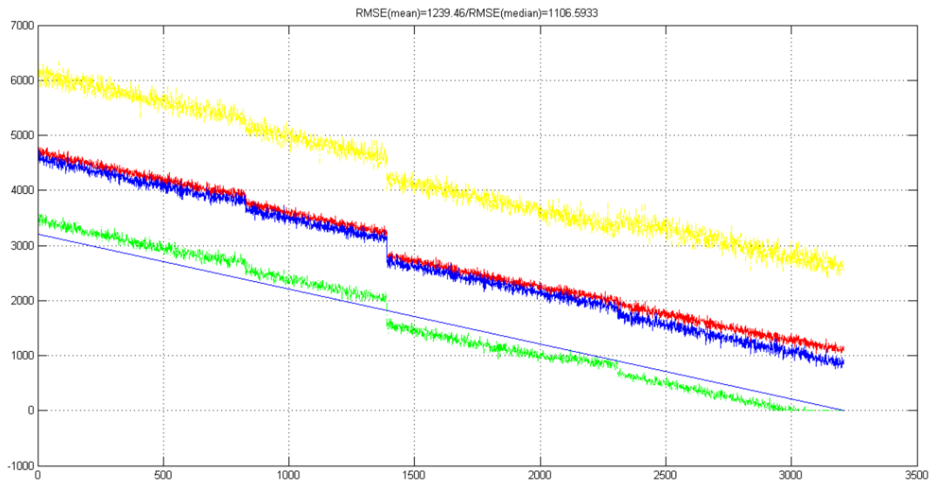

Figure B-4 RUL Prediction result of IGBT No.2 with Combining model

IGBT No.3 RUL prediction results

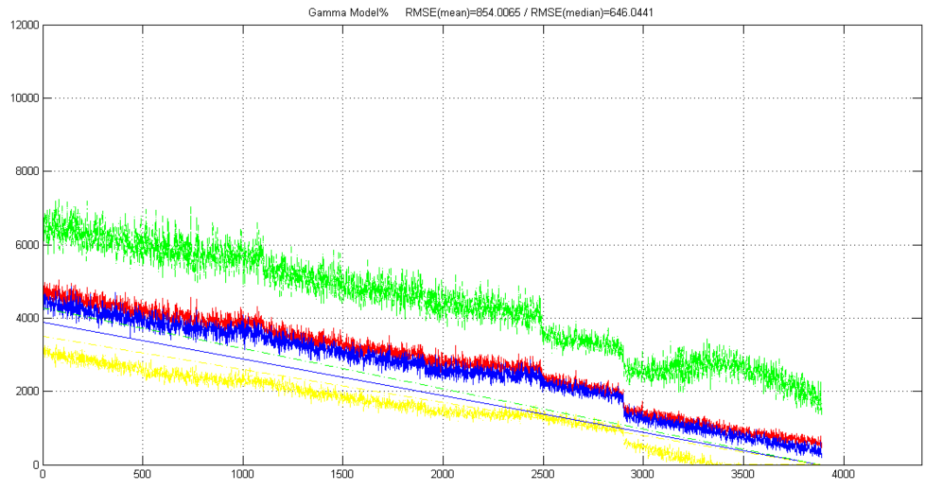

Figure B-5 RUL Prediction result of IGBT No.3 with Gamma model

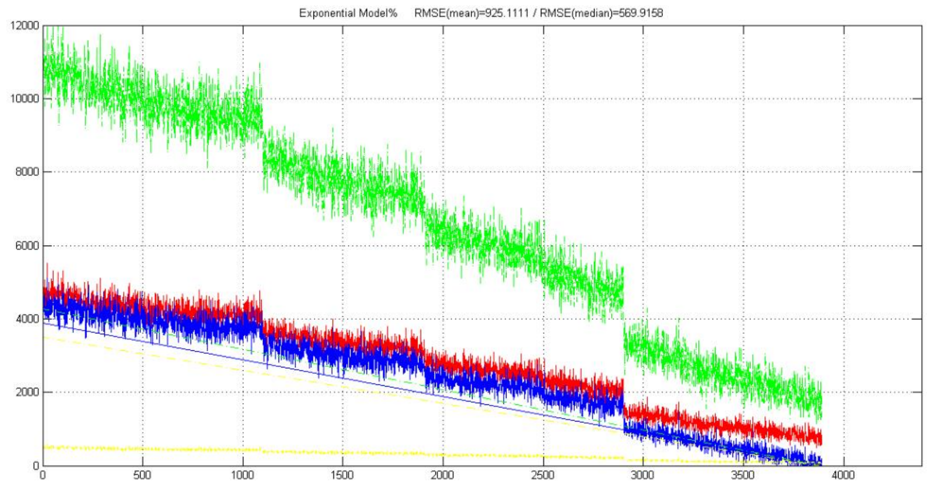

Figure B-6 RUL Prediction result of IGBT No.3 with Exponential model

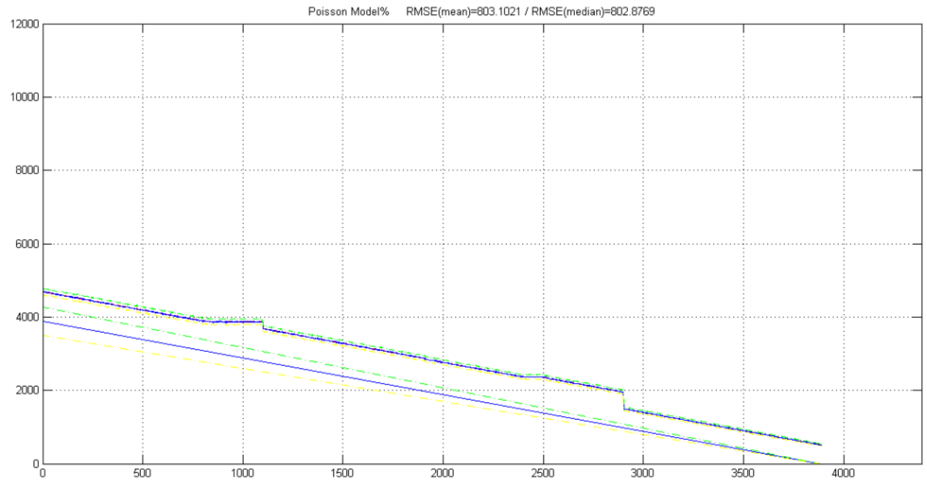

Figure B-7 RUL Prediction result of IGBT No.3 with Poisson model

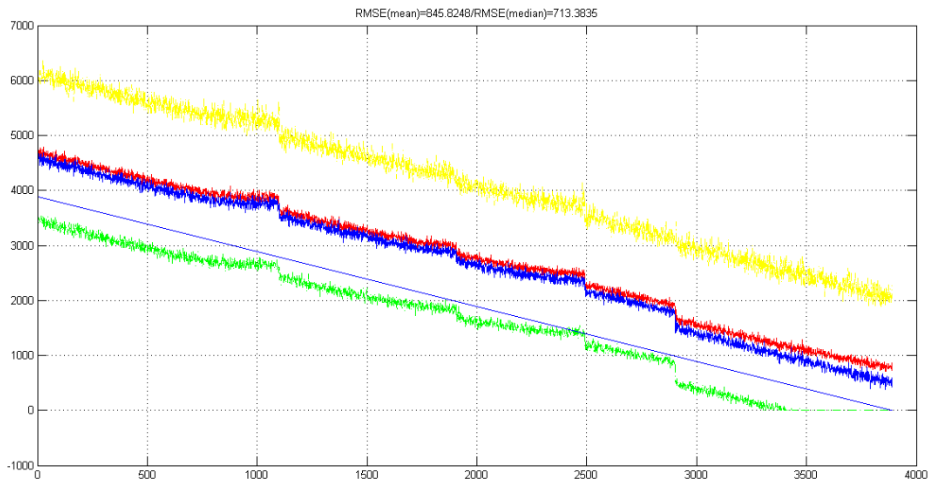

Figure B-8 RUL Prediction result of IGBT No.3 with Combining model

IGBT No.4 RUL prediction results

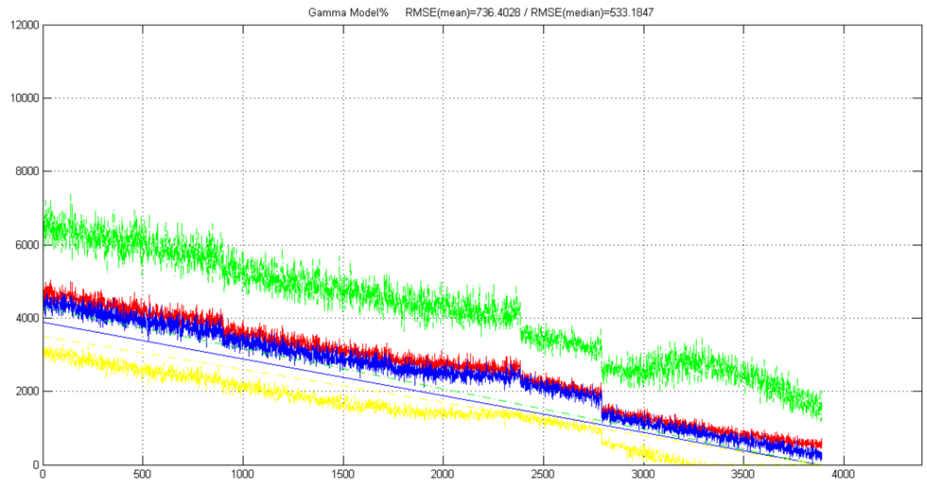

Figure B-9 RUL Prediction result of IGBT No.4 with Gamma model

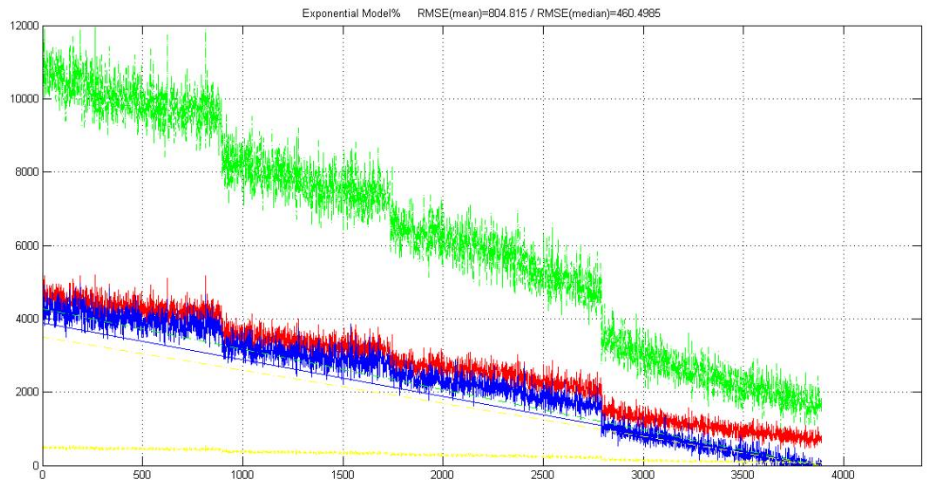

Figure B-10 RUL Prediction result of IGBT No.4 with Exponential model

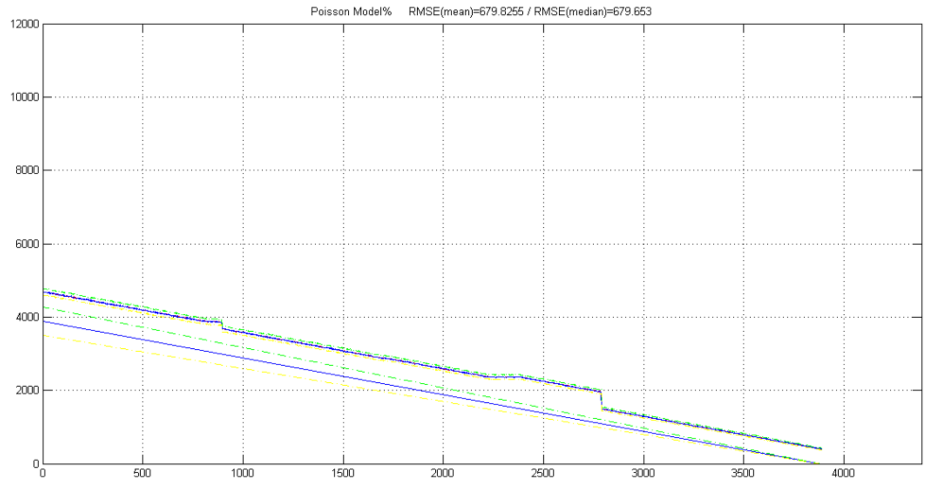

Figure B-11 RUL Prediction result of IGBT No.4 with Poisson model

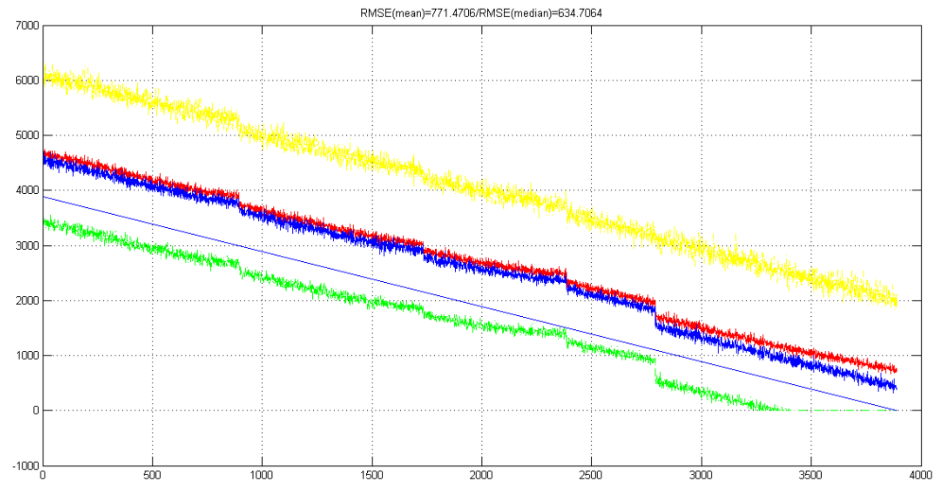

Figure B-12 RUL Prediction result of IGBT No.4 with Combining model

IGBT No.5 RUL prediction results

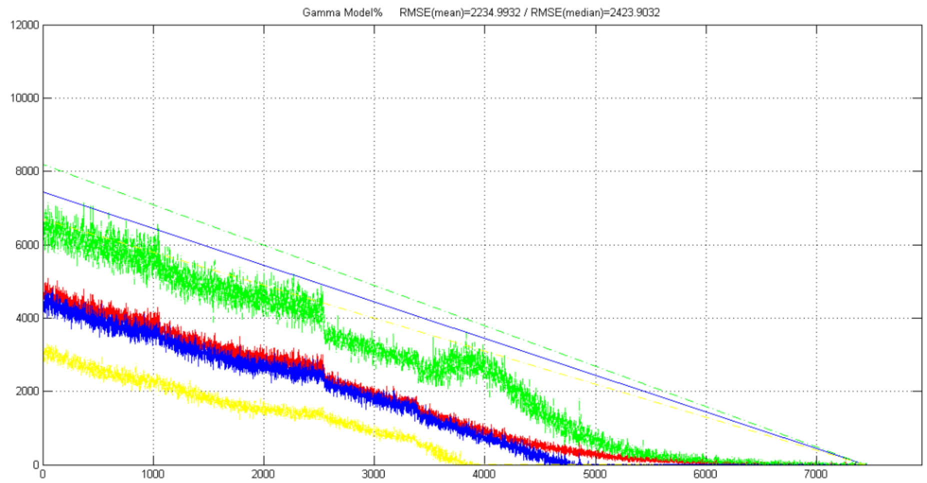

Figure B-13 RUL Prediction result of IGBT No.5 with Gamma model

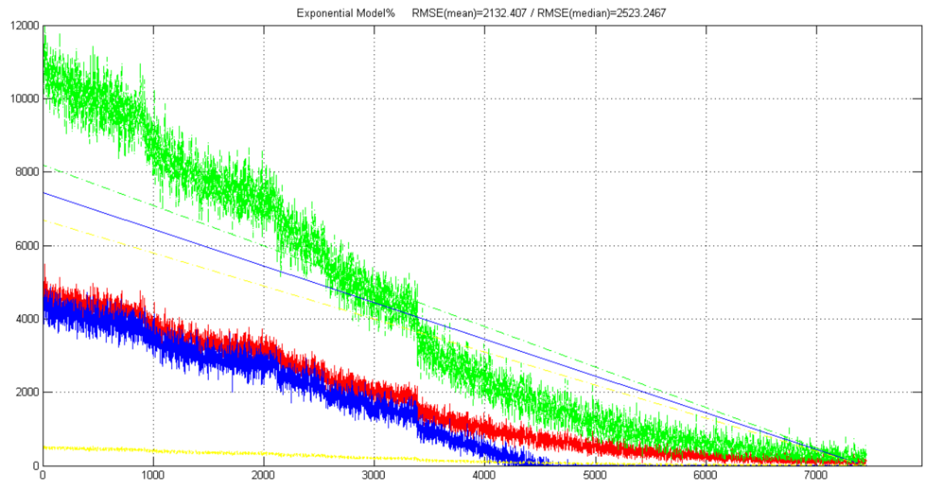

Figure B-14 RUL Prediction result of IGBT No.5 with Exponential model

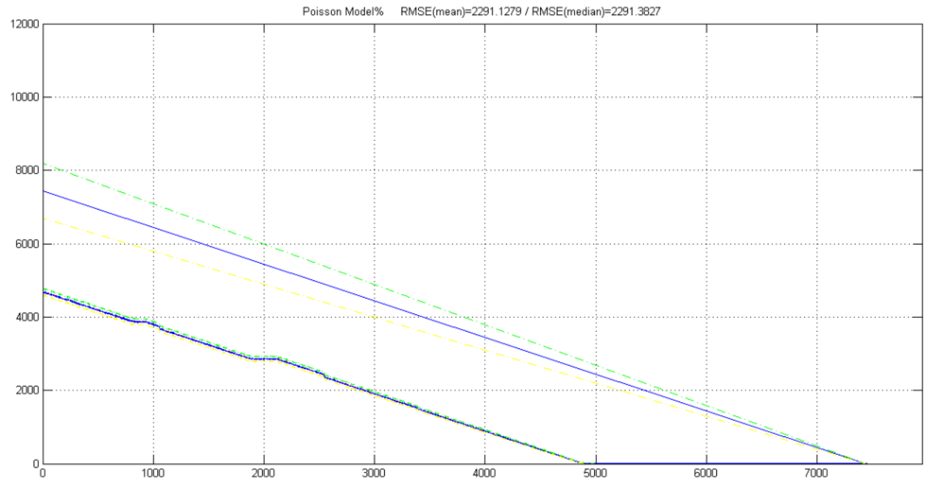

Figure B-15 RUL Prediction result of IGBT No.5 with Poisson model

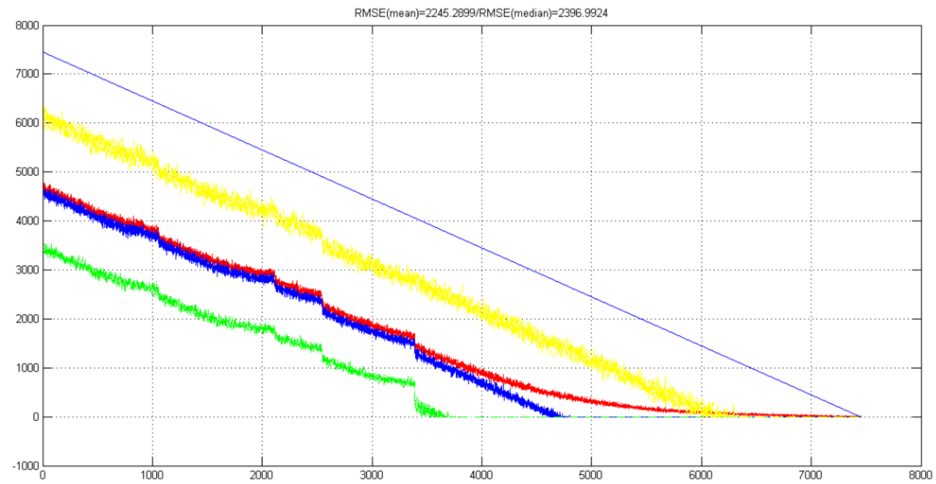

Figure B-16 RUL Prediction result of IGBT No.5 with Combining model

IGBT No.6 RUL prediction results

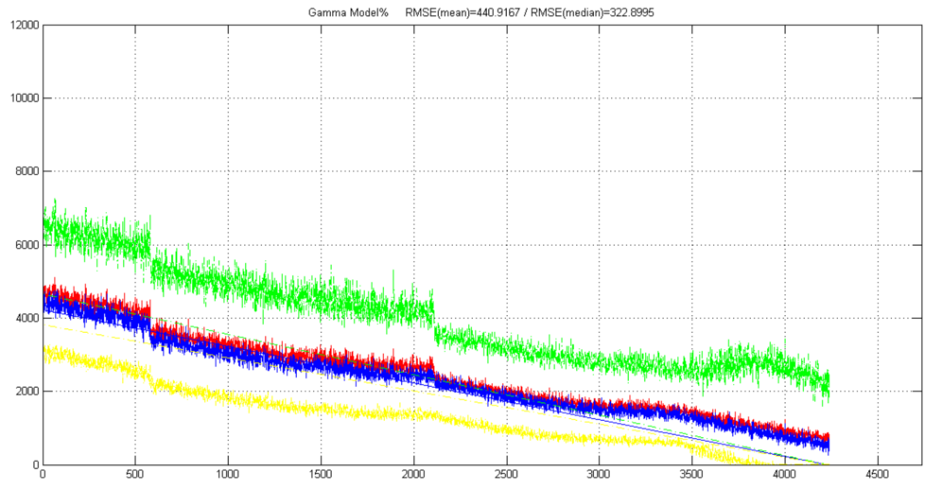

Figure B-17 RUL Prediction result of IGBT No.6 with Gamma model

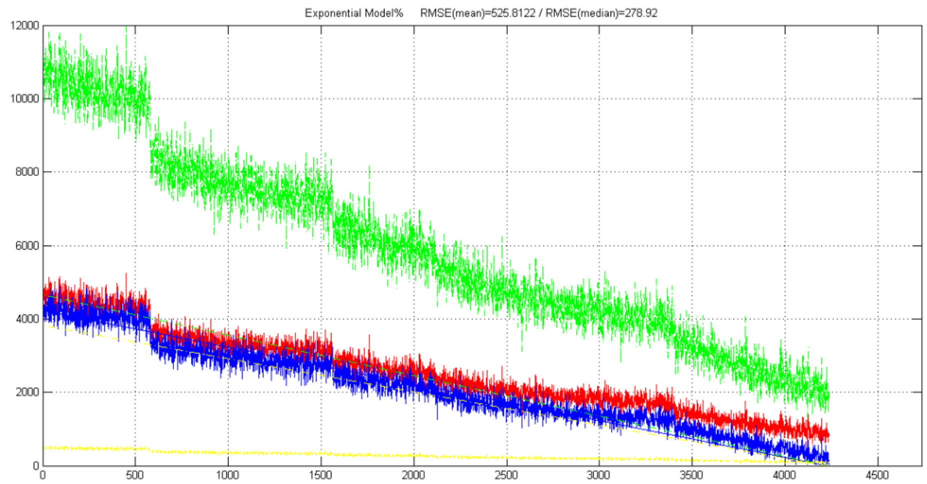

Figure B-18 RUL Prediction result of IGBT No.6 with Exponential model

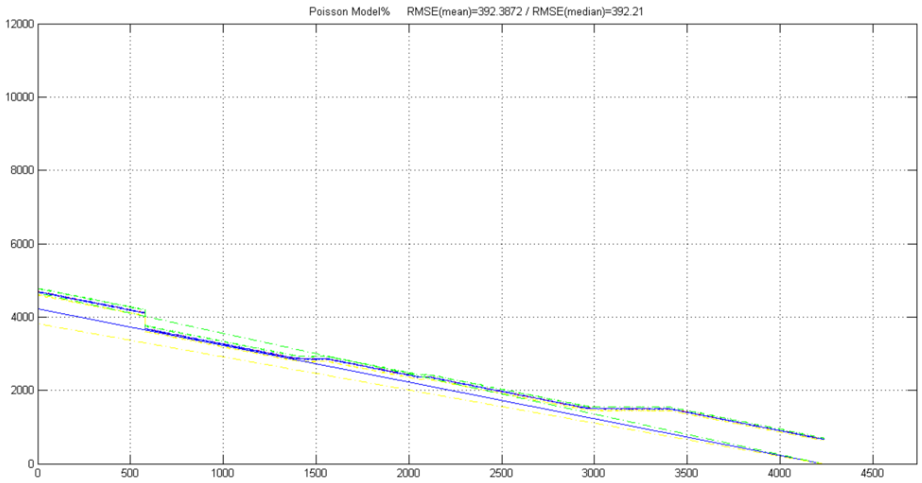

Figure B-19 RUL Prediction result of IGBT No.6 with Poisson model

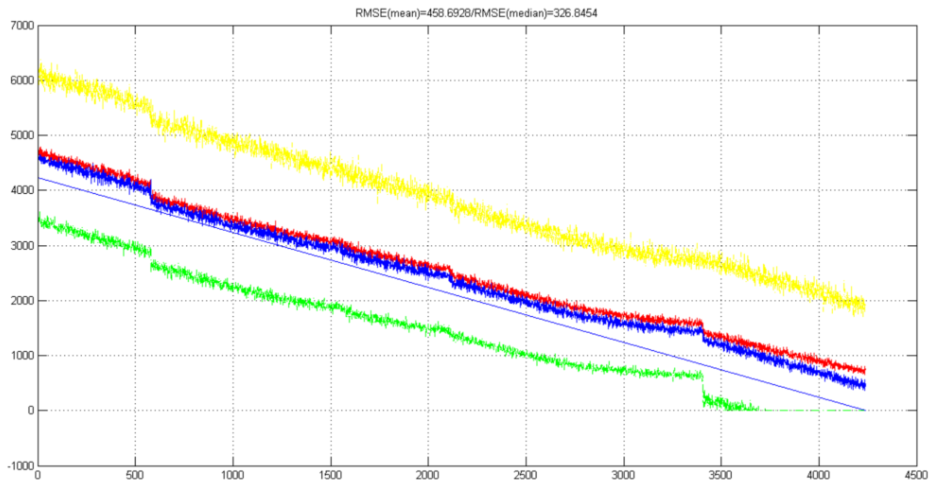

Figure B-20 RUL Prediction result of IGBT No.6 with Combining model

IGBT No.7 RUL prediction results

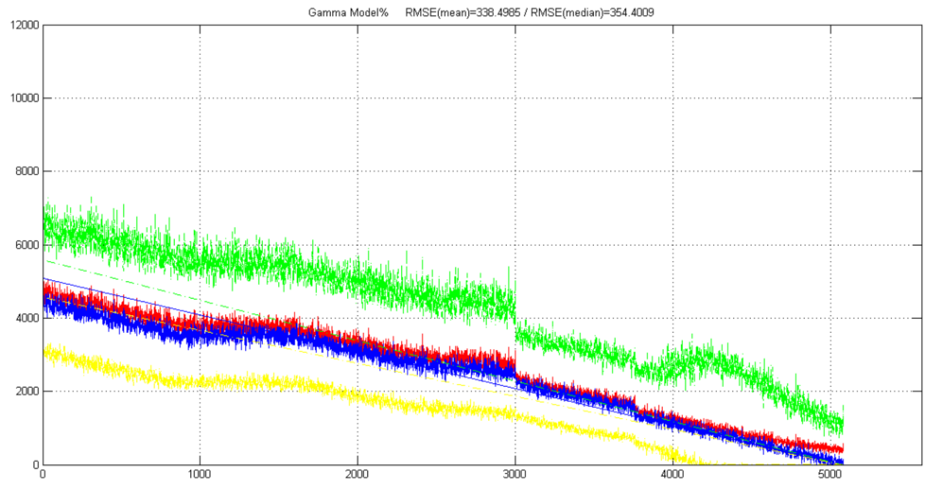

Figure B-21 RUL Prediction result of IGBT No.7 with Gamma model

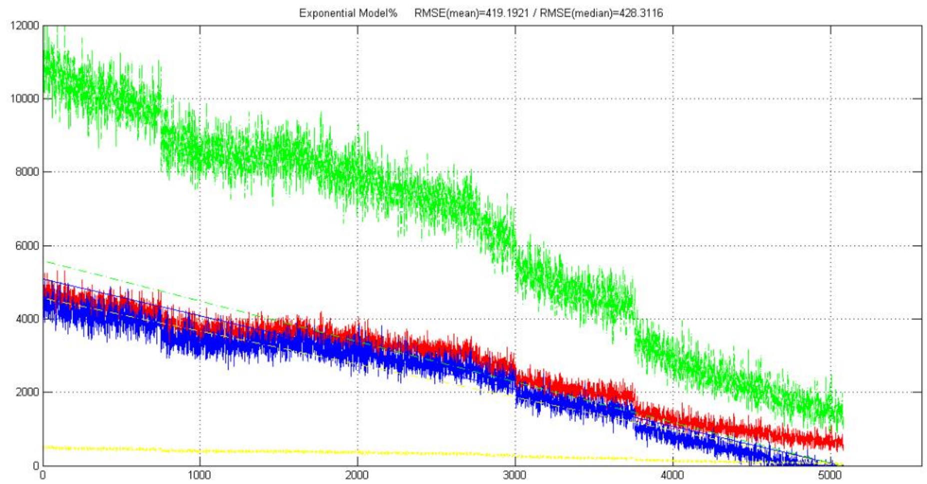

Figure B-22 RUL Prediction result of IGBT No.7 with Exponential model

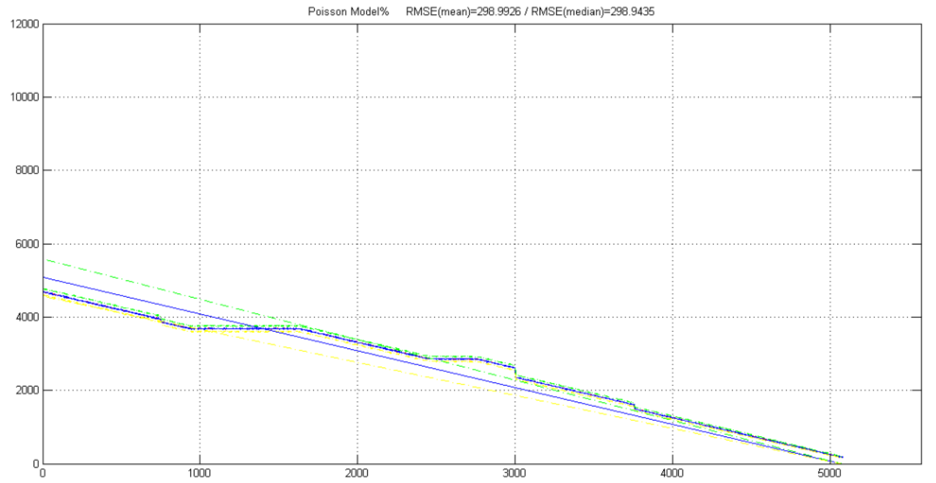

Figure B-23 RUL Prediction result of IGBT No.7 with Poisson model

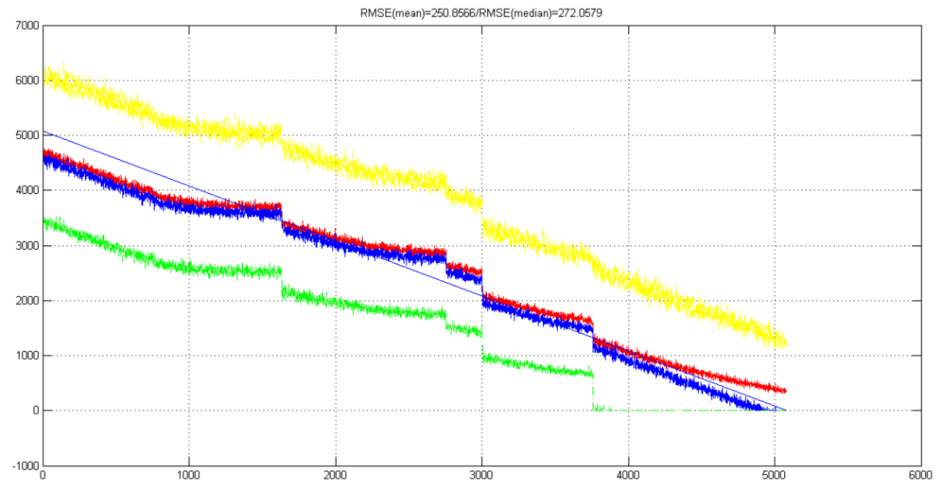

Figure B-24 RUL Prediction result of IGBT No.7 with Combining model