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用於提升電子系統可靠度之貝氏失效診斷法
A Bayesian-Based Fault Diagnosis Method for Reliability Improvement of Electric System

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摘要

隨著汽車智慧化及駕駛自動化的發展，電子系統的可靠度對汽車安全性有著越來越大的影響力。電子系統的運用能協助偵側危險的駕駛行為同時也能適時的輔助一般駕駛者，但這些提升駕駛安全的功能往往因為電子系統在嚴苛的環境下行駛導致可靠度降低進而影響汽車安全性。現存的可靠度分法如故障樹分析及失效模式與影響分析可以協助了解系統破壞的因果關係；馬可夫模型及可靠度分配透過可靠度的計算及量測幫助我們量化失效模式的發生機率。儘管有許多可靠度相關的研究及分析方法，但對電子系統這種失效原因及結果相對複雜的系統而言，要找出每一種失效背後的原因仍是相當困難的，同時現實中對系統失效原因的診斷往往會因為高昂的量測成本而無法達成。

因此本研究欲提出一個找出電子系統最有可能的失效原因的診斷方法：透過物理破壞的角度，分析當焊接點受到環境及人為不確定因素產生電阻偏差值如何影響系統可靠度並找出客觀的失效原因排序；設計者可透過此分析結果進行量測，並透過貝氏更新法快速更新診斷結果，經由慢慢增加量測樣本直到診斷結果及結論得以建立。本研究使用增壓器及變壓 (頻) 器系統做為範例演示整體診斷過程，過程中透過考量環境溫度及電子原件本身的發熱，可以得知電子系統的可靠度會因為開發階段不同的電路板設計和電子原件位置配置而受到影響，透過更改電路的原件配置，可將系統可靠度大幅提升。本研究將分析診斷結果和‘失效模式與影響分析表格 (FMEA)’ 做整合，提供一個明確的系統可靠度改善方向；透過本研究提出的方法可以幫助電子系統在設計開發階段重新檢驗並提升可靠度，並使使用大量複雜電子系統的

產品如汽車能在實際使用實能有更高的可靠度。

關鍵字：可靠度、車用電子系統、物理破壞、量測樣本、貝氏更新法、FMEA。

Abstract

The reliability of electrical systems on modern vehicles has an increasing impact on the on-road safety with then increase of smart technology implementations. These electrical systems help detecting dangerous driver behaviors, alleviate driving errors, prevent unintended actions, as well as provide alternatives to internal combustion engines. The goals of having more efficient and safer vehicles could be undermined by the low reliability of electrical systems at severe driving environment.

Existing reliability assessment methods, such as fault tree analysis and failure mode and effect analysis, focus on the cause and effects of component failure on system faults. On the other hands, Markov-chain based methods and reliability allocation techniques quantifies how these failure modes propagates within a complex system using reliability measure. Albeit abundant research activities, diagnosing the true origin of a system fault among all possible causes can be challenging. Incorporating these results for reliability improvements requires measurements that are costly in product development.

Therefore in this research we develop a method to identifying the most likely origin of a electrical system fault with incremental data using Bayesian concept. We incorporate physics of failure in the welding joints of each components and consider the performance variations within each components. The result will be a subjective probability measure to rank the relative likely cause of a fault under varying environmental conditions. Designers can then use this result to sequentially identifying or measuring the health of each components until a conclusion is made. To deal with reliability with limited measurement samples, a reliability evaluating and updating scheme via Bayesian inference is established.

We demonstrate the validity of the proposed method via a boost converter and an inverter. Consider the product development stage results in a electric layout that is to be realized. We show that due to the ambient temperature gradient and the rise of component temperature in operation, the reliability of a circuit rely on its configuration. We also use the examples to show the effect of the sample size on our probability measure.

Combined with FMEA, the proposed method can help re-examine the electrical system in the earliest design stage toward high reliability target. For modern vehicles with a large number of complex electrical systems, our method can help improving the final reliability in real operation.

Keywords: Reliability, Vehicle electrical system, Measurement data, Physics of failure, Bayesian inference, FMEA

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Chapter 1

Introduction

Chapter 1 presents the background, the motivation, and the organization of this research. Section 1.1 talks about the abundant applications of electrical systems in modern design. However, the reliability in these systems are among the most concerned issues for users and manufacturers. Obstacles in evaluating reliability of electrical systems are presented in section 1.2. The need for research and the motivation of this research are also presented in section 1.2. Section 1.3 shows the structure of the thesis.

1.1 Research background

The implementation of advanced technology in modern products are made possible with complex electrical systems. With the miniaturizing of electrical components, designers can provide a much more compact form of a given space. For example a smart phone consists hundreds of electrical components within a palm-sized PCB board which provides a regular cellular phone with number of additional features. These electrical enables multi-objective in many other products performance requirements.

One of the major application of complex electrical systems are in vehicles. The need of electrical vehicles(EV), including plug-in hybrid electrical vehicle(PHEV), hybrid electrical vehicle(HEV), and battery electrical vehicle(BEV), have risen in past years and is predicted to keep rising in the future as Fig.1.1 due to not only environment concern, energy crisis [1], but also policies and regulations[2]. With the increased need, almost all of the vehicle corporation are now devoted to developing the electrical vehicles and therefore electrical systems had played a more and more important role in vehicle industry in the past few years, for not only basic operation but also the trend of EV being smart and driver-free. Motors in EV are controlled by the motor control unit(MCU), whose quality determines the functionality of the motor system. Another example can be the camera systems of vehicles that are responsible for avoiding frontal and rear crash, ensuring lane keeping, providing driver fatigue warning, among many other safety features that help drivers being aware of the surrounding environment. In addition to these cameras, a standard vehicle also has at least 8 motors that help adjusting the headlight, assisting handling as well as make sure the vehicle provide the best visibility and driving condition for a particular driver. Each of these cameras and motors requires control devices that should be embedded within vehicle body with high reliability.

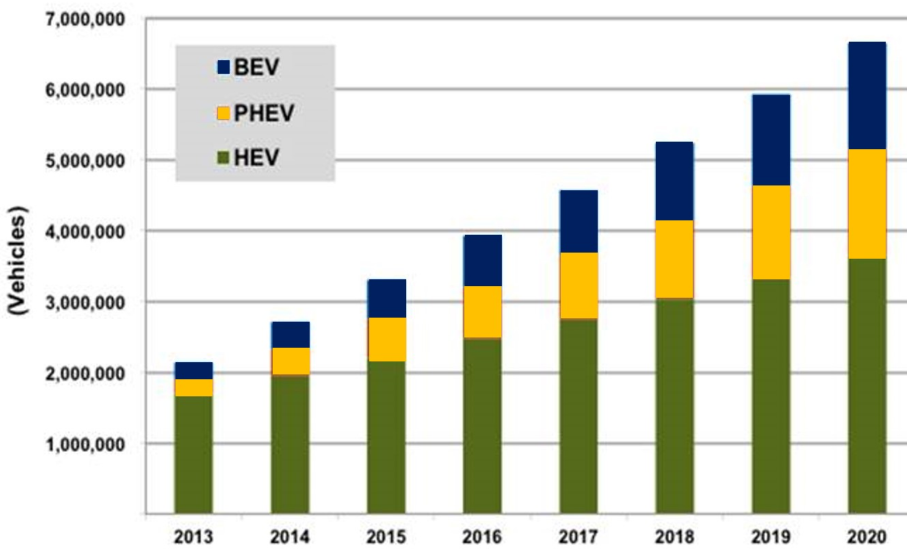

Figure 1.1: Annual (predict) electrical vehicles sales, world market [3]

The implementation of these vehicle electronics aims to reduce car-related accidents. Since these electrical systems are viewed as a ‘safety feature’ that drivers rely heavily on, the reliability of these electrical systems becomes a priority in the development of new vehicles. Otherwise, the advantages of modern drivers’ aides or advanced powertrain systems might be undermined with the inconsistent performance of electrical systems under varying operating conditions.

Unfortunately, one of the main challenge that many automobile corporations faced now is the reliability problem, compared to consumer electronics, electrical systems in vehicles more complex, furthermore, they are exposed to harsher environment such as temperature, humidity, and vibration. The changes in environment might result in variation of amplitude and frequency of output signals, which eventually cause the failure or malfunction of the electrical system, which may cause serious consequences and danger to life. Toyota recalled certain hybrid vehicle models in 2014 due the deformation of the IGBT in MCU from thermal strain causing the electronic control unit to shut down the entire vehicle[4]. Fiat Chrysler Automobiles have recalled Fiat 500e electric cars for fourth time to fix a problem in control unit and software [5]. Upon these evidence, it's obvious that the reliability of the vehicles electrical system should be upgraded as they may lead directly to serious safety concerns. Therefore the aim of this research is to improve the reliability of modern electrical systems.

1.2 Motivation

Improving electrical system reliability in EVs, we have to find out where is the source of failure. With this information we can construct the relation between different failure mode and source of failure and eventually fix failure from the very basic level of source instead of replacing failure item passively as system fails.

Unfortunately, we will face lots of obstacles in finding failure causes of electrical systems. For general electrical systems, different failure causes may cause same item/subsystem in system fails, and failure of different item/subsystem would lead to same failure mode in whole system. All these factors construct a complex cause and effect relation within the system. Therefore it is almost impossible to find the actual failure cause in electrical systems without further assistance. Moreover, **we barely have time and money in reality to detect every region or components within the entire system since the resource is limited**. In reality, every measurement may consume lots of time and money, that makes resource allocation, decide where to measure first, become very important especially for complex system like electrical system in EVs. Furthermore, assume we do know where to take measure, we should be able to "update" our knowledge of the system source of failure and reliability based on these data, however **presented reliability assessment methods can not assess and update reliability through few subsequent measurement data**. The presented methods assess reliability through lots of data in evaluation process, while the measurement resource is limited and the data we can draw are few.

Therefore we need a **systematic approach could diagnose the cause of a failure and suggest subsequent measurement**. In this thesis, we aim to construct a system diagnosis method that can find out the ranking of potential sources of every failure mode. The diagnosis result can then give suggestions on resource allocation and help engineers take measurements with higher efficiency. Furthermore we try to establish a reliability assessment method that can evaluate system reliability with few measurement data are obtained. With the entire propose method one can check whether system reliability is high enough and finally make some improvement on system to obtain a system with higher reliability.

1.3 Thesis organization

Chapter 2 existed system reliability assessment/analysis methods also their defects are presented. Chapter 3 delivers the Bayesian inference that is used to analyze system reliability through limited data. Chapter 4 the entire proposed analysis method is introduced. An engineering case study, boost converter and inverter in electrical vehicles, is used to demonstrate the whole analysis method in chapter 5. Conclusions and future works are in chapter 6.

Chapter 2

System Reliability Assessment and Diagnosis Methods

Chapter 2 reviews the existed system diagnosis and reliability assessment methods also presents the goal of the proposed method of this thesis. Section 2.1 introduces the basic concept of reliability, the reason that we need diagnosis method, and methods in different domains in solving reliability problem. Details of different methods in each domain is then presented from section 2.4 to 2.3. Furthermore the difficulty of presented methods applying in reality with limited data is in section 2.5. Finally, the reason we want to propose a new method and the goal we want to achieve are in section 2.6.

2.1 System reliability assessment and diagnosis

Ideally, performance of product or system can be decided in the design stage. How they work and response from different situation is controlled by the parameters in the system model. Once the parameters are designed and fixed, certain performance of system should be foreseeable. However in reality, uncertainties make the parameters in design stage not be a fixed number but discrete numbers or follow an distribution and they lay in everywhere like manufacturing process or like variation of environment in case of EV electrical system. Since the parameter would vary, the performance of the system may not be as designers expect anymore.

Fig.2.1 illustrates the system performance varies in an interval due to uncertainties acting on system. System performance would not still be fixed but vary as a distribution in the figure when uncertainty act. X-axis is performance(the righter the better) and y-axis is probability density of system performance. Given a performance boundary the acceptable region is then the region that performance is better than boundary(performance on the right side of boundary in the figure). Reliability in define as *the probability of system functional*, that is, the probability of system performance still be in the acceptable region, hence in this illustrate is the region with slash [6]. In traditional reliability analysis, we

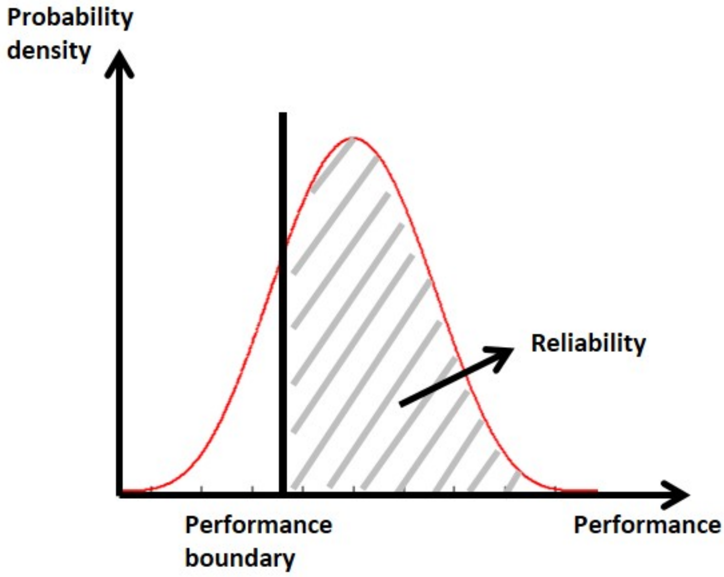

Figure 2.1: Concept of reliability

evaluate system reliability from known uncertainties model and lots of measurement data in design or analysis stage, just like the RBD, Markov Chain, etc. From known model and lots of data the exact number of reliability can be obtained.

To understand the impact of uncertainty on system and improve the system reliability, we need a method to figure out the source of failure that help us understand the interaction within the system, that is, we need a "diagnosis" method. A system illustrate the relations of system input, output, and uncertainty is shown in Fig.2.2. To construct a full understanding of system in uncertainty, we have to achieve two points : (1) Comprehension of system input and output relation. (2) Understanding of uncertainty and its influence on system. As previous paragraph mentioned, complex systems like electrical systems may

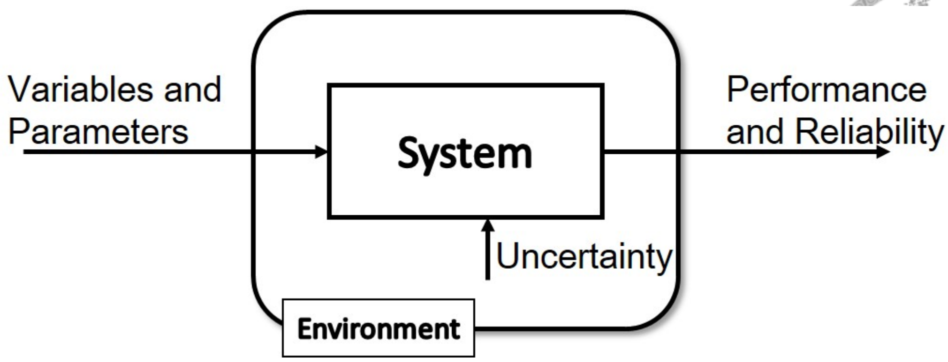

Figure 2.2: System illustration

have different failure modes with similar ‘symptom’ which makes it difficult for us to find the failure causes. A good reliability assessment and diagnosis method should be able to let us understand every failure mode in the system. As we use a good diagnosis method to diagnose all the failure modes in the system, we can construct fully knowledge of failure relation within a complex system even their symptom are same. In our argument, a good method should be able to help us :

1. **Understand input/output relation :** The most important thing to fix any failure mode of system is to know the relation between cause/source (input) and potential failure mode/danger (output). Complete understanding of this relation help us know where to fix the problem and improve reliability.

2. **Predict the influence of uncertainty on system :** The most likely reason to cause a well designed system failure is uncertainty which may lead system performance to an unexpected outcome. Comprehensive knowing of uncertainties and their influence on system help us consider these factors in the early design stage and make sure the system is workable under these uncertainties.

3. **Assess reliability from data :** We usually need to evaluate system reliability with measurement data in reality. Reliability can provide a number of probability that different failure modes occur. With the ability of assess system reliability we can know more of the probability of failure occurs and decide which failure modes to fix first.

Many reliability analysis and diagnosis methods have been developed through out literature review and can be summarized as Table2.1 and classified into different domains that 'mainly' used to : (1) understand input/output relation like fault tree analysis(FTA) and failure mode and effect analysis(FMEA), (2) predict the influence of uncertainty like system diagnosis, and (3) assess reliability like Markov Chain, Petri Net, and reliability block diagram(RBD). After arranging it's obvious no exist general method can achieve all the factors at the same time especially the ability of predicting influence of uncertainty and assess reliability advanced with few samples, which will be introduced in later section. Note that triangle means the method can provide a preliminary while not a complete solution. We will introduce different methods in different domains in detail respectively in the following sections.

Table 2.1: Reliability assessment methods

Index / Method	Understand Input/Output Relation	Predict the influence of uncertainty	Assess reliability from abundant data	Assess reliability from inadequate data
FTA	√		△	
FMEA	√		△	
System prognosis	√	√		
Markov Chain	△		√	
Petri Net	△		√	
RBD			√	

√ : Provide a complete solution, △ : Provide a preliminary solution

2.2 Methods mainly used to understand input and output relation

It is important to understand why a particular failure occur for complex systems with a large number of interacting components. Some methods in this domain try to construct this relation and help users find out failure source directly.

2.2.1 Fault Tree Analysis

Fault Tree Analysis(FTA) uses the same structural concept and deploy the system by linking the individual failure effects at the lower level and the system failure events at the top level. It is a top down, deductive failure analysis of an undesired system state causes by a series of lower-level events. FTA is mainly used to understand how systems can fail, to identify the best ways to reduce risk or to determine event rates of a safety accident or a particular system level (functional) failure. FTA can be used in almost every field and systems like power supply system [7], in [8] Gao et al. extend original FTA to a more practical diagnosis method with a case study on power transformer, or in [9] hydrogen-cooling system is use to demo the ability of FTA.

Fig.2.3 shows the basic graphical expression of FTA. FTA uses and, and or symbols connect the relation between top event(system level failure) and basic even(components level failure). Expand every system failure mode as the illustration and the impact of each component on system can be revealed. With the FTA, engineers can understand which component to fix to improve the system reliability.

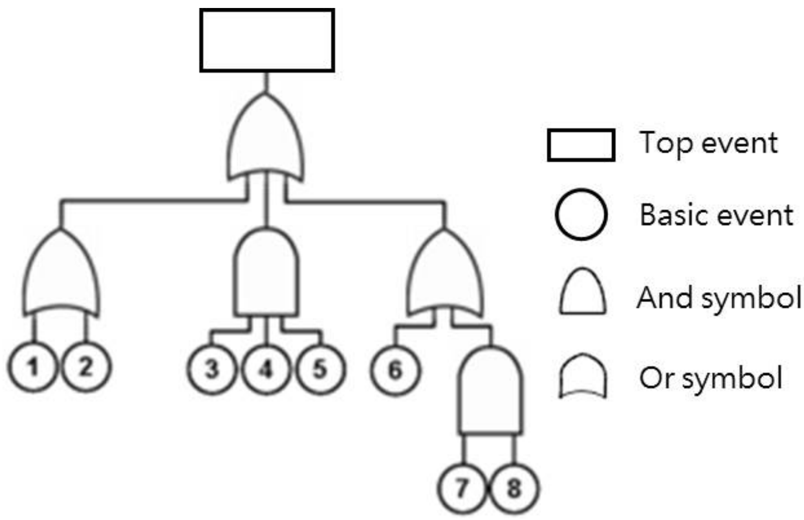

Figure 2.3: FTA illustration

Although FTA can let one know the cause and effect relation of every system failure mechanism, FTA generally does not have the ability of reliability quantification, despite the fact that some researchers make modifications of FTA with more capability of reliability by replacing events with components reliability, so called the probability rate diagram in [10], or incorporate reliability quantification in to FTA with concept of power flow model [11] .

Two commonly-used methods, FTA and RBD, can not *assess reliability* and *show cause and effect relation* at the same time, that leads some restrictions when using : FTA can only find the cause and effect relation while RBD in last domain can assess reliability but unable to show cause and effect relation directly. Therefore, a practical methods needs to provide not only the cause and effect relation but also the quantification reliability value. The next methods, failure mode and effect analysis, give a preliminary solution to this problem.

2.2.2 Failure Mode and Effect Analysis

In terms of comparing the criticality of each failure events, the failure mode and effect analysis uses specific scoring system to compare the impacts of each failure events on the overall system[12]. FMEA provides cause and effect relation of failure mode and basic qualitative analysis therefore is often the first step of a system reliability study for many companies. It involves reviewing as many components, assemblies, and subsystems as possible to identify failure modes, and their causes and effects. For each component, the failure modes and their resulting effects on the rest of the system are recorded in a specific FMEA worksheet. A successful implementation of FMEA allows engineers more aware of why a failure occurs.

Figure 2.4 shows a general layout of FMEA chart in case of electrical vehicle, which contains two parts, the *cause and effect relation* and *reliability quantification*. Left part of the chart shows the potential effect of failure from product level to specific item. This part can provide the same contribution of FTA, furthermore, FMEA give a fundamental reliability assessment, the Risk Priority Number(RPN). RPN is used to determine which part needs to be fixed priorly and is multiplication of SEV (Severity of the event) $\times$ OCC (Probability of the event occurring) $\times$ DET (Probability that the event would not be detected before the user was aware of it). Engineers can decide which failure mode or item to fix first based on the RPN. Take Fig.2.4 as an example, if the engineers find that IGBT open is an easily-detect failure mode, they will mark '2', while this failure mode would cause great danger to vehicles and drivers thus mark '8' at severity. Note that all these numbers follow a standard manual developed by different companies.

Although FMEA is capable in both finding cause and effect relation and quantifying

Function	Failure Mode	Effect(System level)	Effect(Vehicle level)	OCC	SEV	DET	RPN
Item / Function	Potential Failure Mode	Potential Effect(s) of Failure	Potential Effect(s) of Failure	OCC	SEV	DET	RPN
IGBT	Always Open	Motor does not work	Before start:Vehicle stranded	4	8	2	64

Figure 2.4: FMEA chart

reliability, it still has some defect: the scoring standard is objective, furthermore, the multiplication of the severity, occurrence and detection rankings may result in rank reversals, where a less serious failure mode receives a higher RPN than a more serious failure mode. The reason for these is that the rankings are ordinal scale numbers, and multiplication is not defined for ordinal numbers. The ordinal rankings only say that one ranking is better or worse than another, but not by how much. For instance, a ranking of '2' may not be twice as severe as a ranking of '1', but multiplication treats them as though they are. Therefore, a subjective analysis number of reliability is needed in FMEA, with that FMEA will be more practical and that is also one of the main objectives in the thesis.

2.3 Methods mainly used to predict the foresee failures of system

Any failure may cause severe consequence for systems, like E-system in EV, therefore it is important to know under what condition will the failure occur. Methods in the field diagnose the system from analyzing system putout signal and try to find the regular pattern of signal before failure.

2.3.1 System Prognosis

Researchers in the field of prognosis try to predict the future reliability or do the health management of the system from the out put signal of systems. Prognostics is a process of predicting the future reliability of a product by assessing the extent of deviation or degradation of a product from its expected normal operating conditions [13, 14].

Many researchers provide many work based on this concept, Pecht et al. give a general concept of prognosis and health management of electrical system and develop approach of model-based and data-driven [15]. The biggest advantage of this method is that both model-based approach and data-driven are adapted, this give the method more flexibility in practical using. Whereas these methods still get some drawback like the data would never be “sufficient”. In [16] Pecht et al. incorporate the physics of failure into prognosis process, this work achieve almost every factor that should contain in a diagnosis method we mentions in previous section except for providing input/output relation, however this method is a passive method since they fix system only when fault signals are detected. If we can find out the possible failure in the earliest design stage, the method would be more practical.

2.4 Methods mainly used to assess reliability of complex system

Various methods in this domain exist to quantify the risk and failure given the information of system structure and the components within the system.

2.4.1 Markov Chain

Markov Chain use the situation of system at this time instant to predict the performance or reliability in next time instant, furthermore, the situation of system in next instant will only influence by that in this instant and it is a stochastic process. Markov Chain consider the transitions between various states of a components and provide a comprehensive representations of possible chains of failure events. Markov Chain is based on the concept of multi-level-system, analyze the reliability of a system based on how failure, as a state, transits within the structure. The transition matrix, which contains the probability that a system in a certain state at an instant time changes to another state, combined with the failure rate of components help engineers evaluate the long-term system reliability.

Seyedi et al. extend Markov model to be applicable to power transformer protection, combine analysis result with the monitoring and self checking system the power transformer reliability can be enhanced [17]. In [18] a Markov reliability model is used to assess the mean time to failure of the system, the analysis is shown to be simple and useful for assessing the reliability of motor drives and can help in designing fault tolerance mechanisms for specific drives, where reliability can be evaluated after every design.

Although Markov Chain provide a good way to assess system reliability and many researchers modified or expend Markov to be applicable with different kinds of systems, Markov Chain assess reliability directly without considering the interaction within system, therefore, Markov Chain can hardly provide input/output relation directly and predict how the system will be influent by uncertainty.

2.4.2 Petri net

One of main assumptions of Markov Chain is 'future state depends only on present state', which will lead to a drawback that Markov Chain only consider constant rate within transition and does not account for aging. Petri Net, a method applied in many field, can solve this problem.

As Fig.2.5 shows, Petri Net is directed graphs with two types of nodes: the places(expressed as circles, P_i) and transitions(expressed as rectangles, T_j), and arcs connect places with transitions, within places are tokens expressed as filled circles. The changes of system

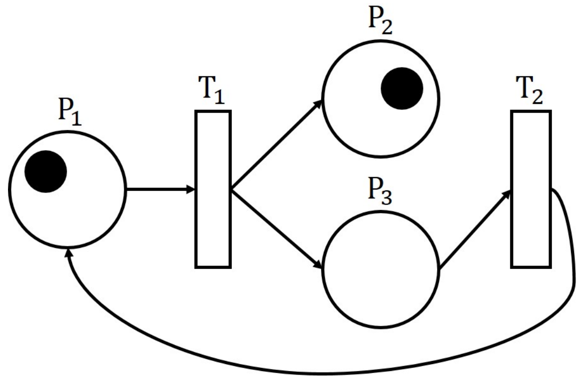

Figure 2.5: Petri Net illustration

state in Petri Net are represented by movements of tokens, which can represent anything like signal flow within the system and its movement are controlled by transitions. Transitions in Petri Net can be functions of time to control system state from one to another, tokens can label to change with time [19], these feature enables Petri Net with ability to handle time dependent problem like Volovoi et al. show the ability of Petri Net in solving reliability problem also the limitation of Markov Chain with a distribution power system [20].

Although Petri Net provide a better vision of Markov Chain with ability of handling time dependent problem, it still not be able to help us know the influence of uncertainty on system. Without this factor, we can still not be able to improve system reliability.

2.4.3 Reliability Block Diagram

The reliability block diagram shows the logical connections between components of the system can be used to understand how information flows within a system[21, 22]. As figure 2.6 shown a system with 3 components, the probability of input signal can flow through the system successfully(λ_{system}) is the multiplication of reliability of each component $\lambda_A \times \lambda_B \times \lambda_C$, note that in RDB the engineers can increase system reliability by *reliability allocation*. RBD can not only be used to further understand the system, it can also be used to calculate the overall reliability of the system based on their parallel/series structure, providing that the reliability of each components are given.

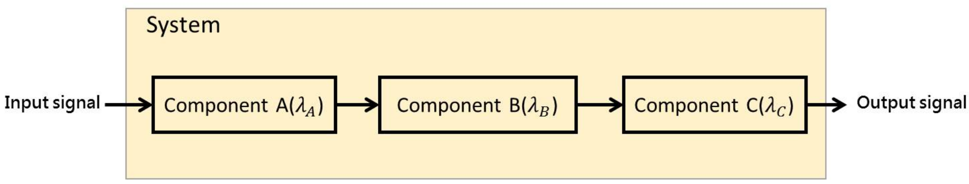

Figure 2.6: Reliability Block Diagram illustration

Despite the fact that RBD provides a simple and direct way to evaluate system reliability, it can not give the illustration of cause (input) and effect (output) relation. Researches on this method usually focus on different promotion of basic RBD like Lin et al. focus on complex system that many components in system are coupling together and propose a method of dividing complex RBD [21], Wang et al. describes the approach of RBD applies to IEEE standard [23], and Zhang et al. combine RBD with importance measure to improve system reliability [24] . Through all literature review, RBD is constructed based on “signal flow” within the system, thus it mainly focus on influence of component reliability on whole system without considering the interaction within the system.

Methods in this domain are mainly used to assess reliability and only focus on the output of the system like in the right part of Fig.2.2. Therefore they generally can not help us understand the input and output relation and how will uncertainty influence the system. These tools, although allow us to quantify risk, are unable to reduce these risk from the basis of component design.

Although we can assess system reliability and deal with many kinds of reliability problems in reality from the concept in Fig.2.1 and methods introduced in previous sections, one big problem has not been considered : these methods are not capable in handling the reliability assessment in measurement field with limited subsequent data. Presented reliability assessment methods usually assume abundant data in evaluation process however in reality we can only obtain inadequate data, which would result in problems introduced in next section.

2.5 Reliability assessment in measurement field with inadequate data

Although engineers can evaluate reliability in analysis stage with the methods in section 2.1, in reality sometimes we have to estimate reliability from few data obtained in measurement field, which will make traditional reliability concept and method fail. From the traditional concept of reliability analysis introduced in Fig. 2.1, the prerequisite is we have an known model for uncertainty. An known model means we can obtain almost *infinite* data, from lots of data we can obtain the reliability as Fig.2.7. However, infinite data is impossible to get in reality. Instead, we can only assess a few data, from the reliability concept fig.2.7 now turns into fig.2.8, which makes the result unreliable since every result may influent a lot by one measurement data. Therefore, the existed methods should be modified to be more adapted to the situation when only few data can be obtained.

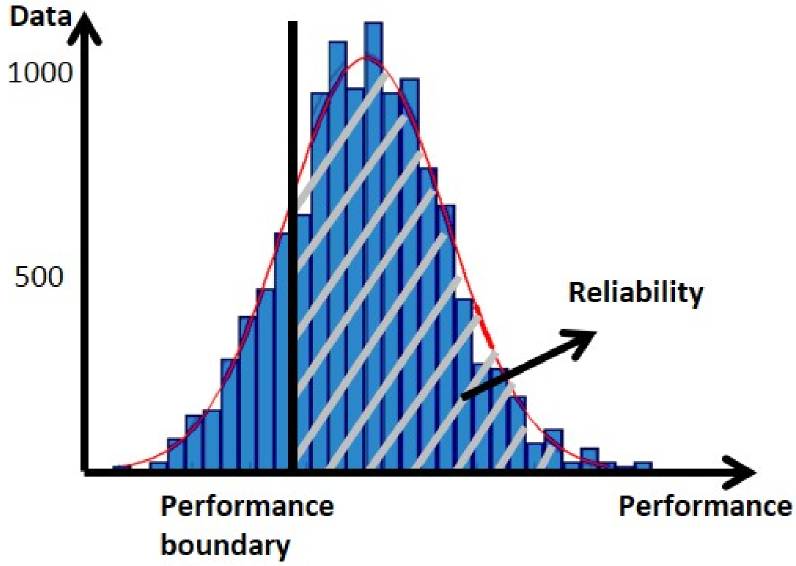

Figure 2.7: Reliability assessment with abundant data

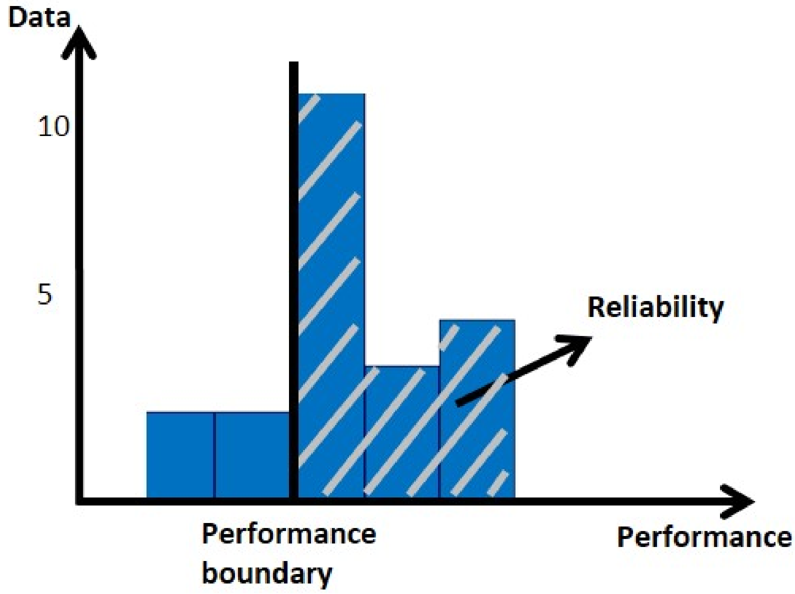

Figure 2.8: Improper reliability assessment with few data

Through literature review, some researchers dedicate in assessing reliability through few samples. Some researchers infer the uncertainty distribution with few measurement data since the measurement data we draw do follow a certain distribution despite that it always remain unknown for us. However it will lead large errors in reliability evaluation if the data are inadequate or the inferred model is improper. Other researchers evaluate system reliability directly without inferring uncertainties model, these researchers use the concept of confidence in reliability evaluation. Some researchers use the Bayes inference [25] in design optimization [26, 27], known as reliability based design optimization(RBDO). Some use this concept dealing with engineering problem like Lin et al. try to find a sampling and resource allocation method in design problem [28], Han et al. deal with pulley system with life data [29]. In this thesis, we incorporate Bayes inference into reliability assessment with few measurement data to make the proposed method more practical. In next chapter, the concept of Bayes inference and reliability estimation process will be introduced.

2.6 Summary

Although we already have these assessment or analysis methods mentioned in previous sections, many of them also be mentioned in literature for example Kavulya et al. present different methods in different domains like *rule-based*, *model-based* etc.[30]. These methods however still can not achieve these goals at the same time :

1. **Understand the impact of uncertainties on the whole system**. One of the reasons that makes some of the systems fail while others are still functional is the uncertainties like environment uncertainties or production uncertainties. Uncertainties would lead unpredictable effects on the system and make the system performance differ from original design, that is, make the system fail even they are all functional in the design stage and the analysis results of "ideal condition". Presented methods show only the results of uncertainties on system but not the link between uncertainties and failure, and that's the first thing need to add in the new assessment method.

2. **Give suggestions on data measurement with higher efficiency in the process of finding cause and effect relation of system**. Since data collection may be resource consuming, a more efficient way to collection data or conduct measurement is needed, a good reliability analysis method should also capable in giving suggestion on data allocation like the way FMEA shows failure item of failure mode. With

new analysis method we can find the most critical causes that make system reliability drop with fewer data.

3. **Assess reliability index through limited samples and update the assessment or analysis results when new data is obtained from measurement field**. From the concept of reliability analysis, the more data is obtained, the more "precise" the result would be. Therefore, it's always a good news that we can measure more data. However, this can not easily be done since in the practical world we are restricted by limited time and money. Therefore, it's likely that we should evaluate reliability through few samples, furthermore, the reliability assessment or analysis should be able to "update" the result as there are more data obtained from the test field. However, the existing methods do not get the ability to solve these problems and that's the other thing that we should add into the new assessment method.

Therefore in this thesis, we will combine one major assessment methods that lots of companies use, the FMEA chart, with the concept of physics of failure and Bayesian inference to achieve all the important factor mentioned in this chapter. With the modification, the new method, Bayesian diagnosis, with result presented in form of FMEA chart can provide (1) relation of input/output, which can used to give suggestions on where should new measurement take under different failure mode, (2) ability of quantifying reliability, which can help engineers decide which failure mode should be fixed first, (3) ability of predicting the influence of uncertainty, which can help to redesign the system with higher reliability, and (4) ability of evaluating reliability with few data, which make the method still available in measurement field when engineers need to update or obtain reliability information with few measurement data.

The concept that we want to incorporate into our diagnosis, Bayesian inference and Bayesian reliability update scheme, will be introduced first in next chapter.

Chapter 3

Bayes inference in Reliability Assessment

One of the main goals in this thesis is to incorporate the measurement data into diagnosis process. By evaluating and updating the reliability model of the system with these data we can make diagnosis result more accurate. The central idea behind these evaluation and updating process is Bayes updating scheme. In this chapter, these concepts will be introduced step by step in each section. Section 3.1 introduces the basic concept of Bayes theorem and updating scheme. The further concept of reliability estimation used in this thesis is presented in section 3.2, and a simple mathematical example is shown in section 3.3.

3.1 Bayesian reliability update scheme

Bayesian inference is used to solve the difficulty of traditional reliability assessment method meets in practical using. One of disadvantages of traditional reliability analysis methods deal with uncertainty in practical using is that they evaluate reliability through large size of data or assume that the uncertainty as an known model, however, both of them are never known for us in reality. For example, we will never completely know the exact performance of each components under uncertainties like temperature, instead, we can only obtain few measurement data under limited time and costs. It is time that existed method fails and the main reason that we need a new evaluation method.

The main idea of evaluating reliability through few samples in this thesis is established on the Bayesian inference. Bayesian inference is an approach based on Bayes theorem, here we introduce Bayes theorem first. In the following subsection the complete derived process is introduced first.

3.1.1 Bayes theorem

Bayes theorem is derived based on the concept of conditional probability as shown in Eq.3.1:

$$\Pr(A|B) = \frac{\Pr(A \cap B)}{\Pr(B)} \tag{3.1}$$

where $\Pr(A|B)$ is the probability of event A happens under the circumstance of event B happens, or the probability of A given B. $\Pr(A \cap B)$ is joint probability of both events A and B happen, and is equal to $\Pr(B|A)\Pr(A)$ from the multiplication rule. Therefore, Eq.3.1 can transfer into Eq.3.2:

$$\Pr(A|B) = \frac{\Pr(B|A)\Pr(A)}{\Pr(B)} \tag{3.2}$$

Furthermore, probability of event B can expressed as :

$$\Pr(B) = \Pr(B \cap A) + \Pr(B \cap A^C) \tag{3.3}$$

where $\Pr(A^C)$ is complement probability of A, by bring Eq.3.3 into Eq.3.2 we can obtain a new expression of conditional probability as:

$$\begin{aligned} \Pr(A|B) &= \frac{\Pr(B|A)\Pr(A)}{\Pr(B \cap A) + \Pr(B \cap A^C)} && (3.4) \\ &= \frac{\Pr(B|A)\Pr(A)}{\Pr(B|A)\Pr(A) + \Pr(B|A^C)\Pr(A^C)} && (3.5) \end{aligned}$$

extend Eq.3.5 to a more general case with multiple events, we have:

$$\Pr(B) = \sum_{j=1}^{k} \Pr(B|A_j)\Pr(A_j) \tag{3.6}$$

the conditional probability of multiple events then result in Eq.3.7

$$\Pr(A_j|B) = \frac{\Pr(B|A_j)\Pr(A_j)}{\sum_{j=1}^{k} \Pr(B|A_j)\Pr(A_j)} \tag{3.7}$$

equation3.7 is the general form of Bayes theorem, $\Pr(A_j|B)$ is the posterior probability, $\Pr(A_j)$ is prior probability, and $\Pr(B|A_j)$ is likelihood. Take dominator part as constant then comes the general idea or expression of Bayes inference:

$$Posterior\ probability \propto Prior\ probability \times Likelihood$$

With this relation, we can obtain or update the new model follows a distribution by simply multiplying two original distributions. Note that in practical using, the prior probability in Bayes inference can be viewed as the model we already have based on the existed data, likelihood is the new data we obtain, and posterior probability is the updated model evaluate from the previous model and new data.

3.1.2 Conjugate prior in Bayes inference

From the previous section, multiplying is the only thing we have to do to obtain new model, however we will meet difficulties in multiplying : as we use X distribution to describe the model that we interested in, and set new data follow Y distribution, from Bayes inference we can obtain the new model in distribution Z by multiplied two distributions, while the process may be complicate since the outcome distribution, Z, of multiplication of even two “simple” distributions, like normal or Poisson distribution, may be hard to evaluate or need lots of parameters to express(Fig.3.1), not to mention the next update.

Most of the combination of prior and likelihood in Bayes inference have same problem which makes inference impractical. Different types of prior distribution and likelihood

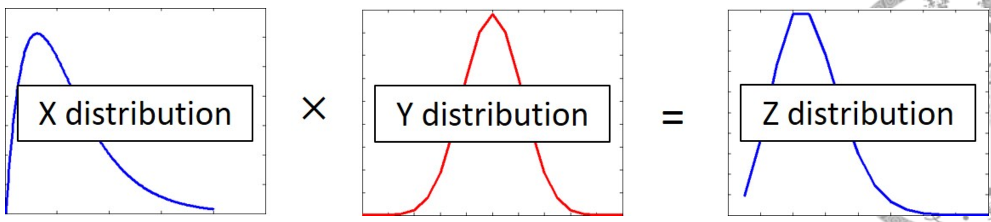

Figure 3.1: Multiplication of distribution

result in different type of posterior distributions. The update concept now meet another problem: which distributions should we choose to make the update process simpler?

In some special cases, the types of prior and posterior distributions are the same(Fig.3.2), these priors are called *conjugate priors*. The biggest advantage of using conjugate priors is that because the original model(prior distribution) and updated model(posterior distribution) are same distribution, the only thing we have to do in evaluation process is to calculate the parameters of distributions. In this thesis we use one of the commonly use conjugate priors, Beta-Binomial, and we will describe for detail in the following paragraph.

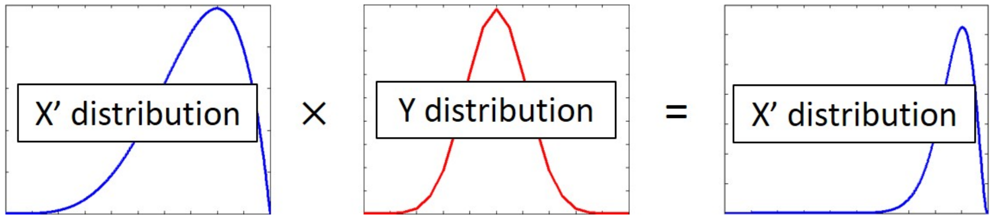

Figure 3.2: Multiplication of distribution in special cases

3.1.3 Beta-Binomial inference

Beta-Binomial inference is mainly applied in evaluating reliability of binary tests, like the pass/fail test of system, in a time instant. That is, Beta-Binomial inference is used to deal with the reliability in a time-invariant problem. Beta-Binomial inference states that when the prior follows Beta distribution and likelihood follows binomial distribution, the posterior will also follow Beta distribution. In this thesis, we model system reliability at a time instant as Beta distribution and new measurement data follow binomial distribution.

Beta distribution

Beta distribution is a continuous distribution of a variable p bounded in the interval [0,1]. With two shape parameters α and β we can have the probability density function(PDF) as

Eq.3.8 where $\Gamma(.)$ is gamma distribution.

$$f(p) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} p^{\alpha-1}(1-p)^{\beta-1} \tag{3.8}$$

some distributions with different parameters are shown in Fig.3.3.

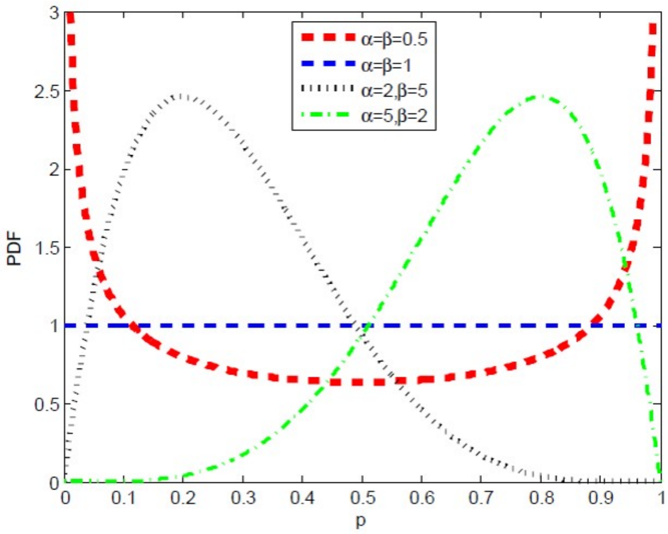

Figure 3.3: Beta PDFs for selected values of parameters α and β

two properties of Beta distribution should be noted that: (1) since Beta distribution is bounded in the interval [0,1], the integral of any Beta PDF in this interval is always 1, also note that this property is same as probability. (2) the Beta PDF with two parameters are both 1 is the same distribution as uniform distribution in the same interval.

Binomial distribution

Binomial distribution is frequently used as probability model of certain sample number appears in a Bernoulli trial. In a Bernoulli trial, the most common example is coin flip, (1) all trials are independent. (2) Each trial results in only two out come “success(survive)” or ”fail”. (3) The probability of success p remains constant in each trial. With N Bernoulli trial, and given probability of success as p, the probability that results in r success events are:

$$f(r|p) = \binom{N}{r} p^r (1-p)^{N-r} \tag{3.9}$$

for $r = 0, 1, \ldots, N$ where

$$\binom{N}{r} = \frac{N!}{p! \times (N-r)!} \tag{3.10}$$

other the detail of these distribution can be found in [31].

Beta-Binomial inference

The Bayes inference states that *posterior probability is proportional to prior times likelihood*, here we use Beta distribution as prior and binomial as likelihood. Therefore the posterior is:

$$f(p|r) \propto \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)+\Gamma(\beta)} p^{\alpha-1}(1-p)^{\beta-1} \times \binom{N}{r} p^r (1-p)^{N-r} \tag{3.11}$$

Eq.3.11 can be viewed as the function of p, therefore the distribution will not be affected by constants that do not depend on p. Hence, the equation can be rearranged as:

$$f(p|r) \propto A \times p^{\alpha-1}(1-p)^{\beta-1} \times B \times p^r(1-p)^{N-r} \tag{3.12}$$

$$\propto p^{\alpha+r-1}(1-p)^{\beta+(N-r)-1} \tag{3.13}$$

Now recognize Eq.3.13 as Beta distribution with parameters $\alpha' = \alpha+r$ and $\beta' = \beta+N-r$, we find that we only need to add the number of successes to α and that of failure to β of new data as:

$$f(p) = \frac{\Gamma(\alpha+\beta+N)}{\Gamma(\alpha+r)\Gamma(\beta+(N-r))} p^{\alpha+r-1}(1-p)^{\beta+(N-r)-1} \tag{3.14}$$

$$\propto p^{\alpha+r-1}(1-p)^{\beta+(N-r)-1} \tag{3.15}$$

compare Eq.3.13 with Eq.3.15 we found that both distributions follow Beta distribution, just as last paragraph states. With this relation, we can update our model by simply changing the parameters of the distribution, which is far more simple than do the integral in every evaluation.

3.2 Reliability estimation via Bayes inference

Constraints in engineering field, or known as performance boundaries, contain parameters with uncertainties which we can only get few data from measurement field in the reality. Therefore, all these data should be used effectively to estimate the reliability. In this thesis, we use both known parameter model obtain theoretical exact reliability value and a more conservative one with few data via Bayesian inference. In the previous section the Bayesian inference is used to evaluate the reliability and update as new data is obtained. In this section, the reliability estimation process will be introduced in detail.

3.2.1 Reliability estimation

We use Beta distribution as the model of reliability. Before any measurement data is obtained, the prior would be a beta distribution with α and β are both 1, or uniform distribution. This can be viewed as without any measurement data, the probability of reliability in any system from 0% to 100% is equal to 1. After obtaining new data, which follow binomial distribution, as likelihood, the updated reliability model, the posterior, can be accessed as:

$$f(p|r) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)+\Gamma(\beta)} p^{\alpha-1}(1-p)^{\beta-1} \tag{3.16}$$

where $\alpha = r + 1$ and $\beta = (N - r) + 1$, that is, the updated model of reliability is Beta($r + 1, (N - r) + 1$). Eq.3.16 can be used iteratively to update p as the new N and r are obtained and added.

Some of reliability distributions are shown in Fig.3.4, as previous paragraph mentioned, Beta distribution is an uniform distribution when there is no data obtained, as the red line. As the data are added, the reliability distribution would approach to a certain value, and that more as more data are added, like the trend of red line to blue, and to solid black line in the figure. This also reveal an important concept: the more data added, the reliability distribution will converge more to a certain value. The meaning of reliability function converging to a value is that we have more 'confidence' that reliability is in a smaller range or value. Furthermore as the number of data approach to infinite, the reliability function will converge to a value which is same as that of traditional reliability assessment method obtained.

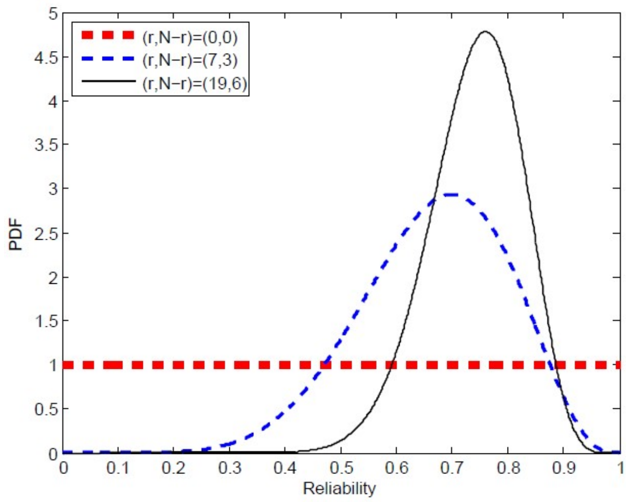

Figure 3.4: Reliability function with different sample size

3.2.2 Confident range

The reliability function is established in subsection 3.2.1, however we still need one more step to complete the estimation process. When the uncertainty model is known, we can get the exact reliability value, while with few data, what we get is a distribution of reliability. Hence we need to add one more factor to transfer distribution into comparable value. The factor we add is the "reliability target(R_t)", which is defined by the designer on how high the system reliability is needed. By adding the reliability target, we can integrate the probability that larger than the reliability target, which is defined as confident range(CR), as shown in Eq.3.17 and Fig.3.5. Where Φ_{Beta} is the cumulative density function of beta distribution given reliability target, parameter α and β.

$$
\begin{aligned}
CR =& \Pr(R \geq R_t) \\
=& 1 - \Phi_{Beta}(R_t, \alpha, \beta)
\end{aligned}
\tag{3.17}
$$

We can now obtain a comparable value from distribution of reliability function with Eq.3.5, in this thesis we compare confident range in different scenario under the circum-

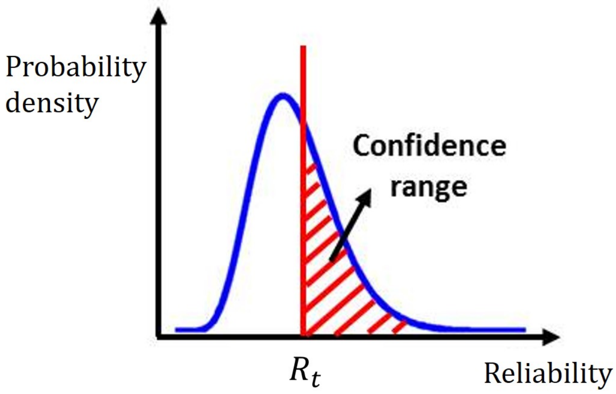

Figure 3.5: Confident range of reliability function

stance of few data is obtained.

We can construct reliability function and compare them when only few measurement data are obtained with all the information in this section , a simple mathematical example is used to show the assessment process in next section.

3.3 Reliability estimation example

Here we take a simple mathematical example to demonstrate Bayesian reliability inference. Let a constraint $G(P_1, P_2) = 1 - 80/(P_1^2 + 5P_2 + 2.09) \leq 0$ with two parameters follow Gaussian distribution, $P_1 \sim N(-8.2, 0.08^2)$ and $P_2 \sim N(2.2, 0.02^2)$, while we assume we don not know the real distributions but only few samples from these distributions. The reliability target is set to be 0.7. We demo this case this two scenario : first with 5 samples and add 5 more in the second scenario. The samples of parameters are in table3.1.

Table 3.1: Samples of P

P_1	Initial samples	-8.2755	-8.2537	-8.1539	-8.3669	-8.1811
	Additional samples	-8.2623	-8.1120	-8.2684	-8.1994	-8.2750
P_2	Initial samples	2.1864	2.1948	2.1954	2.1895	2.2226
	Additional samples	2.2110	2.2371	2.1945	2.2213	2.1580

Scenario 1: with 5 samples

In this demonstration we use the concept of “sample combination”, which means under condition of parameters are independent, we can combine parameters together. For example in scenario 1 both parameters contain 5 samples, this means we have $5 \times 5 = 25$ combinations. After iterating the total number of successful events r =16. From Bayesian the reliability function is then **R**$\sim$ beta$(r+1,(N-r)+1)$ = beta$(17,10)$ and the confident range would be $1 - \Phi_{beta}(0.7, 17, 10) = 0.2295$.

Scenario 2: add 5 more samples

To show how reliability function and confident range change with more samples, we add 5 more samples at both parameters. With totally 10 samples in both parameters, we have $10 \times 10 = 100$ sample combinations, $r = 76$ in this scenario, the reliability function is then beta(77,25) and confident range become $1 - \Phi_{beta}(0.7, 77, 25) = 0.8978$.

Scenario 1 is the reliability function with 25 combinations and scenario 2 with 100 combinations. As shown in Fig.3.6 it can also easily be seen that confident range of scenario 2 is better than 1 since the area of scenario 1 distribution larger than 0.9 is larger than that of 2. In this example we show the more samples we can get, the higher the confident range would be also the more precious the estimation of reliability distribution would be. In this thesis we use this technique to evaluate system reliability through few samples.

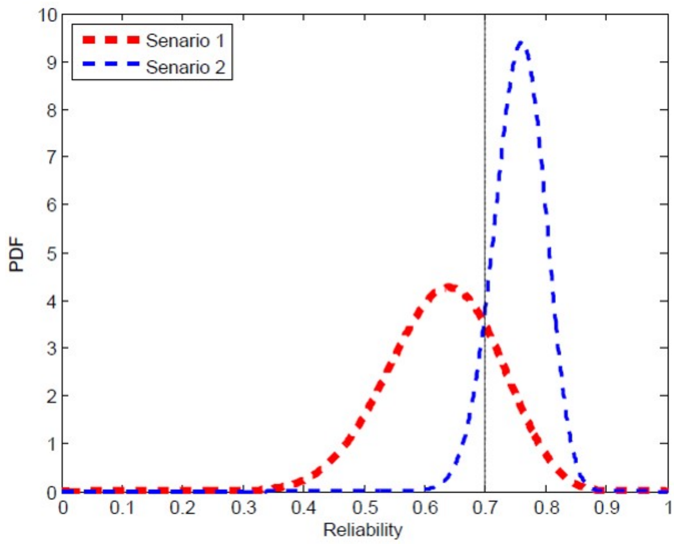

Figure 3.6: Reliability function of two scenarios

With reliability update scheme in this chapter we can let our diagnosis method with more ability. In next chapter, the complete diagnosis method is established, also how the Bayesian is incorporated into diagnosis method is also introduced.

Chapter 4

Proposed Diagnosis Method

Chapter 4 proposed a new diagnosis method from the concept of physics of failure. Section 4.1 shows the entire diagnosis flowchart. Section 4.2 presents the central concept we use in diagnosis method. Section 4.3 shows the main diagnosis process : construction of solder joint resistance model, diagnosis objective and method, measuring suggestion based on analysis result, update system reliability with measurement data via Bayesian, and finally system reliability improvement. A summery in given in section 4.4.

4.1 Overall diagnosis flowchart

Figure 4.1 is the flowchart of overall analysis and diagnosis method. We mainly apply the concept of physics of failure, which is also a main electric system reliability analysis method that we have not introduced until next section, into our diagnosis process. **One of the main purposes of proposed diagnosis method is to incorporate few subsequent measuring data into system reliability assessment.**

The first step of diagnosis is to obtain the (1)parameter of solder joint which can be used to construct solder joint resistance model and (2)system circuit model and definition of failure which can let us reproduce failure modes. With these informations we can then use Monte Carlo simulation to evaluate system reliability under different conditions and obtain analysis result. The analysis result can provide measurement suggestions for engineers in measurement field. After assessing new measurements (real solder joint resistance) and simulating with these data, Bayesian updated scheme is then used to assess system reliability with these data. We can then use the confident range of different reliability function to rank the real potential causes of failure. If the ranking is not clearly established, we have to obtain more data from testing field and update reliability again until the ranking is clearly established.

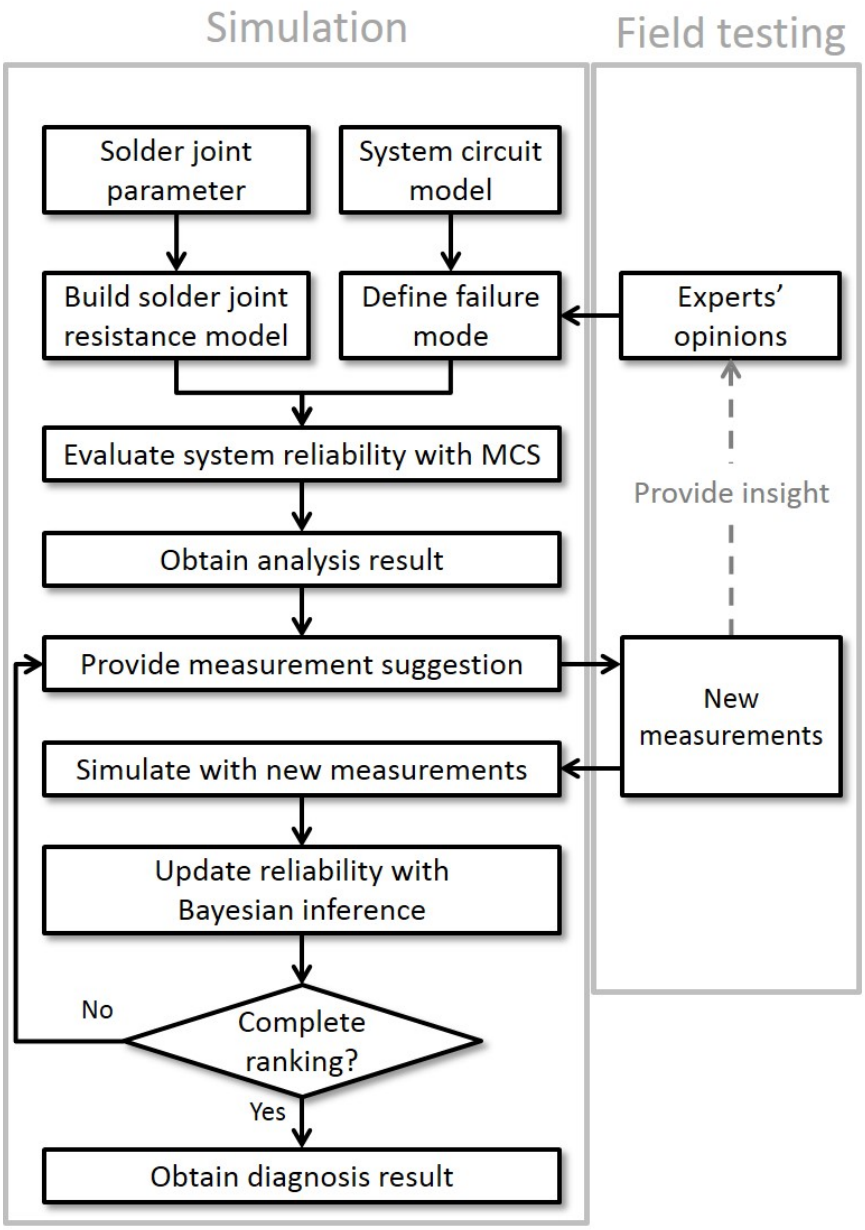

Figure 4.1: Overall diagnosis flowchart

The complete diagnosis process is now introduced, in next section the central diagnosis concept we use will be introduced.

4.2 Diagnosis concept: Physics of failure

Another domain in assessing electrical system reliability did not mention in chapter 2 focuses on physics of failure of the system. Some common methods use component reliability from [32] based on the observations of field measurements to assess system reliability. These methods focus on the impact of "solder joint" on system. For every electric systems they are composed by the basic board, electric components, and solder joint that connect board and components. In addition to components companies try to develop products with higher reliability under harsh environment condition, some researcher focus on the reliability problem of solder joints.

Methods in understanding the physics of failure(PoF) of components focus on modeling the failure of solder joints under different environment with different material compositions[33]. For example, some researchers try to establish solder joint life model by conducting experiments under different thermal cycle or composed by different material [34, 35, 36, 37]. Others try to construct theoretical life model [38, 39] from an important theory, the Engelmaier Model[40].

Understanding the real case of these failures enables design engineers to improve system reliability not only from changing the structure of the system, but also from the very basic elements of failure events.

However in reality, many failure cases show that electrical systems fail even none of component in system fails. One of the reason may be the fault signal accumulation within the system: as the environment uncertainties influent the electric components, the function of them may offset a little from the expected value, however there are not "fail". As most of the components' performance offset a little it may generate a large fault for the entire system and eventually cause failures. In this thesis we focus on the performance variation of an important component of system : the solder joint resistance instead of electric components. Detail of system diagnosis method from the aspect of solder joint will be introduced in next section.

4.3 Diagnosis methodology and process

Although most research activities focus on how the crack within these solder joints initiated and how they propagated toward failure, our goal of applying PoF of solder joints is to understand how the environmental condition changes the performance of these joints. In electrical systems, the healthiness of these solder joints also influent the electrical signal that passes through them.

In electrical systems, solder joints not only are the connection of components and board but also can be viewed as a stereoscopic wire that transmit the signal. In our argument, the most important parameter in wire is the resistance, as the resistance in wire get too large is may influence not only current or voltage but also the signal within system. Unfortunately, it is resistance in solder joint that would be influenced as exposed to harsh environment. When the signal is influence by the resistance in solder joints, electrical system may face situation that none of the component but the system fails. Therefore in this thesis we **analyze system based on the concept of system performance influenced by resistance in solder joint.** From this concept we can find the critical region in working environment and the probability of failure occurs.

4.3.1 Model of solder joint resistance

To simulate a not 100% healthy solder joints, we use "virtual resistors" attached to each component as shown in Fig.4.2. When temperate changes, the component performance varies and so do the connectors. We use the model of solder joint developed by Liu and Ni in [41].

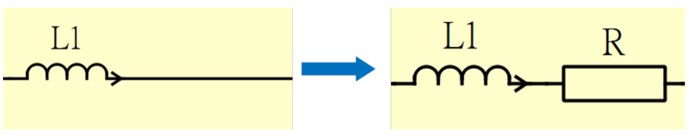

Figure 4.2: Adding the virtual resistor next to inductor

Figure 4.3 shows the complete physical model of a solder joint in five segments pad-film-solder joint-film-pad, which is constructed by Liu and Ni. The corresponding resistor values (R_p, R_s, R_f for pad, solder joint, and film respectively) are calculated from the equations from (4.1) to (4.4). With all the geometric and material parameters in table 4.1 and given rise temperature ΔT (more detail will be given in next subsections) we can obtain the resistance in solder joints at every temperatures. Note that in this research we use the value in table which is from [41].

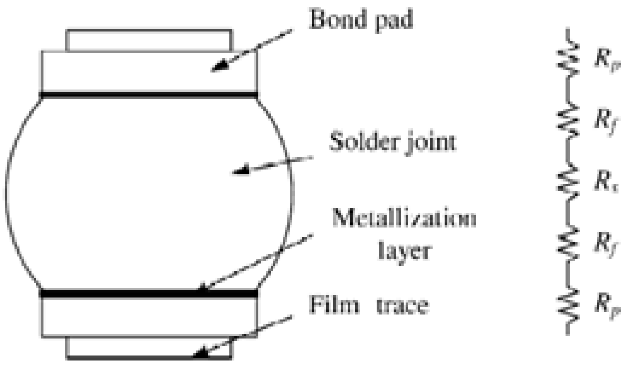

Figure 4.3: Geometry of solder joint

$$\mathrm{R} = 2(R_p + R_f) + R_s \tag{4.1}$$

where

$$R_p = \frac{\rho_p h_p}{A_p}(1 + \beta_p \Delta T) \tag{4.2}$$

$$R_f = \frac{\rho_f}{A_p} \tag{4.3}$$

$$R_s = \frac{3\rho_s h_s^2}{4\pi r_s^3}\exp(\varepsilon^K)(1 + \beta_s \Delta T) \tag{4.4}$$

Furthermore, in soldering process it is almost impossible to obtain identical solder joints. The shape (geometric) and material may not all be the same in every solder joint. Therefore in our study, we consider the variations of parameters in solder joint due to manufacturing as uncertainty (uncertainty during soldering process). We use a Gaussian distribution as Eq.4.5 to construct complete model of solder joint resistance, where the mean value is the ideal resistance use the design parameter at given temperature, and standard deviation is used to model the manufacturing uncertainty. Note that with higher

Table 4.1: Parameters of solder joint

Parameters	Symbol	Value
Thickness of the pad	h_p	$0.0073\ mm$
Cross-sectional area of the pad	A_p	$0.304\ mm^2$
Spherical radius of the solder joint	r_s	$0.38\ mm$
Standoff height of the solder joints	h_s	$0.512\ mm$
Resistivity of the bond pad	ρ_p	$2.65 \times 10^{-5}\ \Omega mm$
Resistivity of the solder joint	ρ_s	$1.45 \times 10^{-4}\ \Omega mm$
Film resistivity	ρ_f	$0.1\ \Omega mm^2$
Temperature coefficient of resistivity of the bond pad	β_p	$0.0016/°\text{C}$
Temperature coefficient of resistivity of the solder joint	β_s	$0.00029/°\text{C}$
Resistance correction factor for shear deformations	K	2.5

quality in soldering process, the standard deviation would be power.

$$\mathrm{R}(T) \sim N(\mu(T), \sigma^2) \tag{4.5}$$

where $\mu(T)$ is the resistance as a function of temperature T obtained from Eq.4.1, and the σ is fixed at 0.00375.

After constructing the resistance model, standard sampling techniques such as Monte Carlo Simulation can be used to access the reliability of a system once their uncertainty at different temperature level is given.

4.3.2 Analysis the critical region of certain failure modes

From subsection 4.3.1 the solder joint resistance model can be obtained as the geometric and material parameters are given, however another important factor has not been drawn into Eq.4.1 yet, the temperature. At what temperature should each solder joint be can be decided from analysis goal, to find the critical region that makes system fail we rise temperature of different parts of system respectively. If system reliability drop a lot as temperature of certain region rises, we claim that this region be temperature sensitive region. Then the ranking of each critical region (solder joint) may be ranked by the correspondence system reliability. Note that in this analysis method for complex system, temperature may have to rise higher than actually working temperature since the influence of individual solder joint would be relative small for a complex system.

This analysis shows an important result : the ranking of critical region, this result reveal which part of system is most likely to make system reliability decrease as temperature rises. With this result engineers can understand the cause(input) and effect(output) relation and make improvement on system.

4.3.3 Analysis the probability of failure modes occur

There would be lots of failure modes in a more complex system. In addition to knowing the which part to fix a certain failure mode, it is also important to know which failure mode is more likely to occur. Existed reliability assessment method did not focus on how uncertainty influence reliability, here we try to figure out how system reliability would be influenced by the temperature that system is exposed.

To known how temperature influence reliability, we have to know at what temperature would system usually be. The major heat source for electrical system is the **ambient temperature**, in case of electrical system in EVs are generated by the motor. Therefore in this diagnosis, the ambient temperature should be obtained first. Furthermore, for any electrical system another heat source would be heat dissipation within components, the components' self heating. Components' self heating come from **power dissipation**, after the power transfer from electrical to thermal, it will not dissipate due to thermal resistance of components. Without proper heat sink the temperature of system would become higher and higher. The temperature of different components are derived from the Equation below:

$$\theta_{JA} = \frac{T_J - T_A}{P_D} \tag{4.6}$$

after rearrange the temperature of solder joint is:

$$T_J = T_A + \theta_{JA} \times P_D \tag{4.7}$$

where

θ_{JA} is the thermal resistance of different components,

T_J is the junction temperature,

T_A is the ambient temperature,

P_D is the power dissipation of components.

Note that all junction temperature of one components are same and we assume solder joint temperature same as junction temperature of each component. Also note that power dissipation is the multiplication of current, voltage, and efficiency of the components.

With all these component informations, temperature of every component solder joints can be obtained and can be viewed as another heat source, we use ANSYS to simulate thermal conductivity within the system and get the *real temperature gradient* of entire system. After obtaining the exact temperature of different part in system we take temperature of different components into equation 4.1 to 4.5 to obtain the complete resistance model as use Monte Carlo simulation to evaluate system reliability or probability of failure occurs.

4.3.4 Suggestion on new measurement

After analyzing, we present the result by adding result in last two subsections into original FMEA chart as Fig.4.4 shown. The new FMEA can provide two new features: a ranking of relative critical region as temperature rises and an "objective" probability of failures occur. With these features, engineers can understand more about which failure is more likely to happen and which part should be fixed. Furthermore, engineers can allocate more measurement resource on top causes in ranking under limited resource and find true cause with higher efficiency.

Ranking of critical region	Item/Function	Failure Mode	Effect(s) of Failure	Probability of failures occur	OCC	SEV	DET	RPN

Figure 4.4: The modified FMEA chart

From previous subsections, we have constructed a diagnosis method that analyzes system with aspect of PoF, and more important is the result can be used to give suggestions to engineers in measurement field to find the reason that cause system fails with fewer resource. In the following subsections, we will show how to update out diagnosis result based on few measurement data we get.

4.3.5 Diagnosis via Bayesian update scheme

After getting new measurements based on analysis result, we use these measurements to simulate with our model again and obtain the system output data (survival and failure number). After obtaining these data, here comes another challenge : how do we update our result with these 'real' data? From last chapter, we have established a reliability assessment method via Bayesian inference. With Bayesian, we can construct the reliability function, which presents how system reliability influenced by a certain failure cause, and obtain confident range from reliability function and the diagnosis result can be completed through these reliability function and confident range. Note that in this process we only use Bayesian to find the ranking of critical region of certain failure mode.

While in some cases, reliability functions constructed from these data would be same like shown in Fig.4.5. Red-solid line and blue-dash line represent reliability function of two performance boundaries. With only 10 samples, two functions are same, this represent with these data we can only know the influence of two failure causes on the system are same and would make ranking infeasible. In this special case, we will suggest engineers in measurement field to sample more data to make them "separate" from each other like in Fig.4.6. As all the reliability functions are separated, the ranking can be obtained and the diagnosis result can also be obtained.

4.3.6 Reliability improvement

With diagnosis result from last chapter, we now have constructed complete understanding of system failure modes. The ultimate task is to enhance system reliability. The diagnosis method in this thesis mainly consider the impact of temperature on system, hence to improve system reliability with diagnosis result, the main concept is to **decrease the temperature of critical region** like improve heat dissipation, or change layout of circuit. With this modification we can actually keep system from failure as temperature rises.

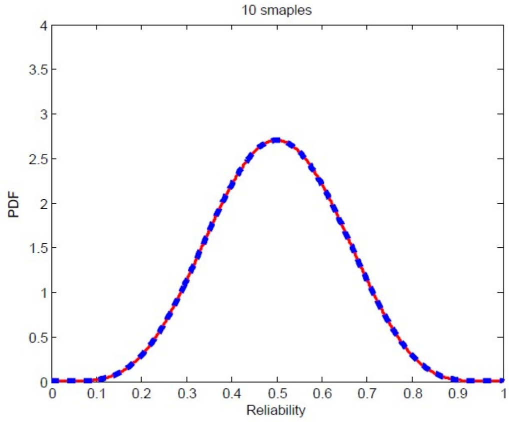

Figure 4.5: Two identical reliability functions

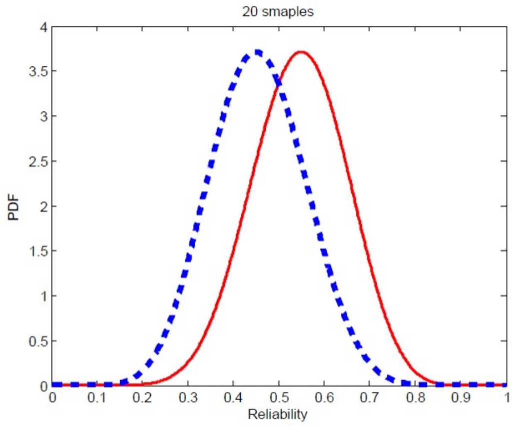

Figure 4.6: "Separate" reliability functions with more data

4.4 Summary

The new diagnosis method, Bayesian diagnosis, is established in this chapter. The main purpose of diagnosis is to find most likely source of failure modes, with this knowledge engineers can decide which part to take measurement first under limited resource in the measurement field, Bayesian inference can help engineers evaluate system reliability with few measurement data and recheck the analysis result. System reliability can be improved based on the analysis result in the end. In next chapter, two cases are used to shown the entire diagnosis process.

Chapter 5

Case Study

Chapter 5 shows the diagnosis method through two cases : common failure mode of EV and high reliability system. Section 5.1 demonstrate two different failure items have same effect on electrical vehicles, from case 1 the influence of very basic solder joint on the entire EV are found. In this case two failure items are demonstrate in subsections 5.1.2 and 5.1.3 in following orders : Model description and performance requirement, diagnosis in analysis stage, measurement suggestion from diagnosis result, result update via Bayesian inference with new measurement data, and finally reliability improvement. Section 5.2 shows the obstacles that the diagnosis method may face when dealing with high reliability problem. Summary are given in section 5.3.

5.1 Diagnosis of failure modes on electrical vehicle

5.1.1 Identifying failure modes & possible causes

Assume engineers get a FMEA chart of an electrical vehicle with two failure modes as Fig.5.1. From the original FMEA chart we know the vehicle stranded may be caused by two failure modes : incorrect voltage level caused by boost converter and incorrect current level caused by the inverter. Note that we assume two failure modes are independent. As we want to solve the problem of vehicles stranded, engineers can barely get any information from this chart. First, the failure items are boost converter and inverter, however from

Item / Function	Failure Mode	Effect(s) of Failure	OCC	SEV	DET	RPN
Boost converter	Incorrect Voltage Level	Vehicle stranded	4	8	6	192
Inverter	Incorrect current leval	Vehicle stranded	4	8	4	128

Figure 5.1: Original FMEA chart of EV

this chart we can not get the information how much and why these item influent system reliability. Furthermore, although the RPN number of two failure modes are different, the number of probability of failure occurs (OCC) and severity (SEV) number are same, which makes engineers hard to decide which failure mode to fix first or where to measure since their symptom, the effect of failure, are same.

In this case study, we try to construct fully understand of these failure modes : find out the critical causes of each failure items and the objective probability of failure occur. With the analysis result we can know more about the failure mode of the EV and make some improvements. Two failure item are analyzed respectively in following two sections.

5.1.2 Failure due to boost converter

A Boost Converter is a DC to DC power converter that use in many practical fields to boost voltage to a desired level with small space occupied instead of using series connections of batteries. The circuit and configuration of a general boost converter are shown in Fig.5.2 to Fig.5.3. Note that the battery in Fig.5.2 is used to represented input voltage.

Performance boundary

The boost converter has a performance requirement that output voltage has to be high enough. Therefore the failure mode is output voltage lower than the performance boundary as equation shown below, as the output voltage is lower than 18.3 volt, we define the system is fail.

$$Voltage \geq 18.3(V)$$

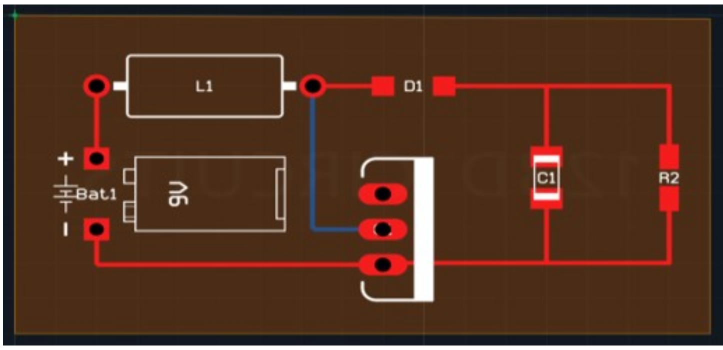

Figure 5.2: Configuration of boost converter

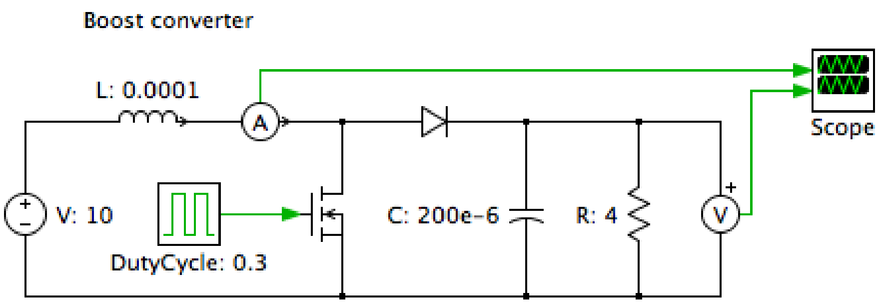

Figure 5.3: Circuit of boost converter

5.1.2.1 Major causes of boost converter failure

Firstly we try to find the critical region of boost converter that make it fail. We rise the temperature of one part of system to 90 degrees every time, at the same time keep other regions at the original temperature (20 degrees), with temperature of all solder joints we can use Eq.4.1 to 4.5 to build resistance model in the system like equation below shows we rise temperature at resistor and keep temperature at other region at 20 degrees:

$$\begin{aligned} \mathrm{R}_R(90°\mathrm{C}) &\sim N(0.1007, 0.00375) \\ \mathrm{R}_C(20°\mathrm{C}) &\sim N(0.0238, 0.00375) \\ \mathrm{R}_L(20°\mathrm{C}) &\sim N(0.0238, 0.00375) \\ \mathrm{R}_D(20°\mathrm{C}) &\sim N(0.0238, 0.00375) \end{aligned} \tag{5.1}$$

with model of solder joint resistance we can assess system reliability respectively, Monte Carlo simulation is applied with 1000 samples from the solder joint resistance model in this stage. Figure 5.4 shows the boost converter reliability with constraint of output voltage should be high enough. From the figure it can be seen that as temperature rises at region where inductor and diode soldered system reliability may drop larger then that of capacitor and resistor, which barely influenced by high temperature. Then we can make the diagnosis conclusion of critical region: **inductor>diode>capacitor=resistor**.

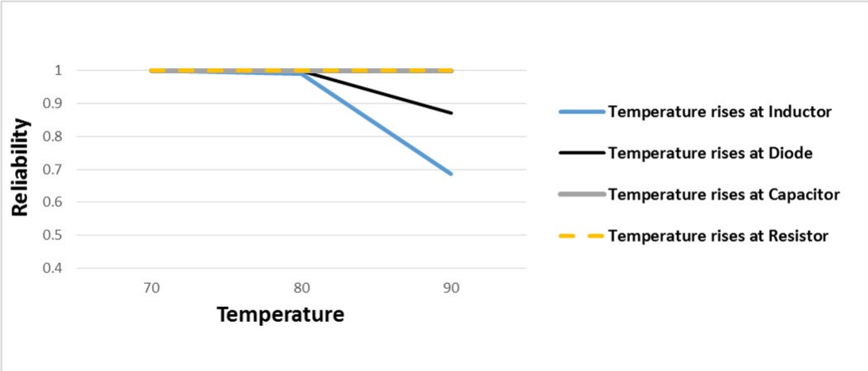

Figure 5.4: System reliability as temperature of different parts rise

5.1.2.2 Probability of failure in a boost converter

Temperature of solder joints

Next we try to find the probability of failure occurs under working temperature. The real working temperature should be obtain first, the ambient temperature that boost converter exposed are shown in Fig.5.5

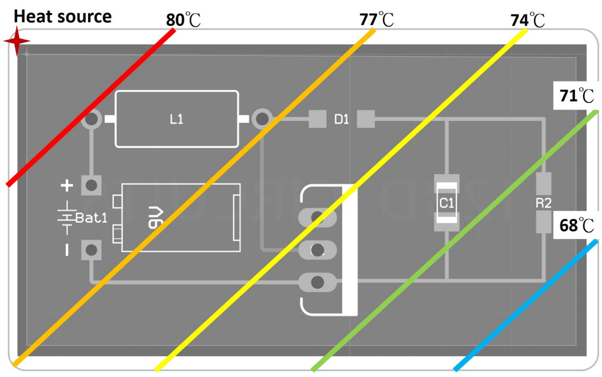

Figure 5.5: Boost converter in working environment

the thermal resistance(°C/W) of each component can obtain from data sheet as:

Resistor=77.1[42]

Capacitor=10.23[43]

Inductor=75

Diode=75[44]

For the boost converter, the current and voltage of each components are:

Resistor : 3(A)&13(V)

Capacitor : 1(A)&13(V)

Inductor : 5(A)&0.265(V)

Diode : 4(A)&3.75(V)

assume that the efficiency all components is 99% thus the power dissipation of resistor is: $3 * 13 * (1 - 0.99) = 0.39$ and that of capacitor, inductor, and diode are 0.13, 0.013, and 0.15 respectively.

With all the parameters, the temperature(°C) of solder joints of different components can be evaluated as equation below, where $T_J(*)$ is the temperature of solder joint attached to component $*$.

$$
\begin{aligned}
T_J(R) &= 68 + 77.1 \times 0.39 = 98.06 \\
T_J(C) &= 71 + 10.23 \times 0.13 = 72.32 \\
T_J(L) &= 77 + 75 \times 0.013 = 77.97 \\
T_J(D) &= 74 + 75 \times 0.15 = 85.25
\end{aligned}
$$

take these temperature as other heat source, we use ANSYS to simulate the working condition, result is shown in Fig.5.6, thermal thermal conductivity of PCB is set to be 0.5 W/mK. Note that in this figure we only show the solder joint of important components and also hide the components on PCB board to make the result more clear.

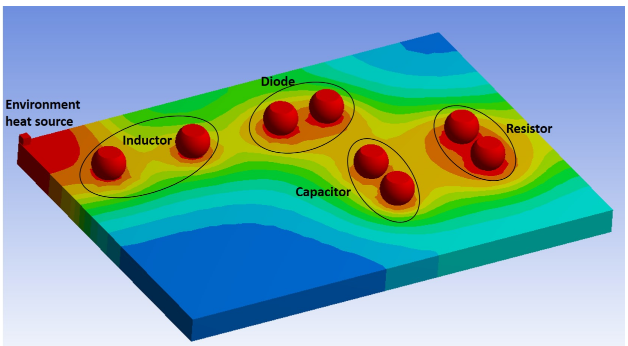

Figure 5.6: Temperature gradient analysis result of original layout

we use probe in ANSYS to get the final temperature, with simulation we can update the real temperature as:

$$\begin{aligned} T_J(R) =& 98.079 \\ T_J(C) =& 76.334 \\ T_J(L) =& 78.068 \\ T_J(D) =& 86.01 \end{aligned} \tag{5.2}$$

System failure probability simulation

Take temperature of each solder joint in Eq.5.2 into Eq.4.1 to 4.5 we can construct complete solder joint resistance model of different components at different temperature as:

$$\begin{aligned} \mathrm{R}_R(98.079°\mathrm{C}) &\sim N(0.1040, 0.00375) \\ \mathrm{R}_C(76.334°\mathrm{C}) &\sim N(0.0754, 0.00375) \\ \mathrm{R}_L(78.068°\mathrm{C}) &\sim N(0.0809, 0.00375) \\ \mathrm{R}_D(86.01°\mathrm{C}) &\sim N(0.0897, 0.00375) \end{aligned} \tag{5.3}$$

Finally, we take 1000 samples from each model and utilize MCS to obtain system reliability. After simulation the system reliability under constraint of output voltage in working temperature is 0.443, therefore, the probability of failure occurs would be 1-0.443=0.557.

5.1.2.3 Diagnosis result in analysis stage

After diagnosing, we can add the result to original FMEA chart as Fig.5.7 shown. Two new features can provide a ranking of relative critical region as temperature rises and an objective probability of failures occur. With these features, engineers can understand more about which failure is more likely to happen and which part should be fixed.

Possible causes	Item/Function	Failure Mode	Effect(s) of Failure	Probability of failures occur	OCC	SEV	DET	RPN
Inductor>Diode> Capacitor>Resistor	Boost converter	Incorrect Voltage Level	Vehicle broke down	0.557	4	8	6	192

Figure 5.7: Modified FMEA chart of boost converter

5.1.2.4 Subsequent measure-and-diagnose approach

Data collection

The first feature in modified FMEA is give a ranking of relative critical region as temperature rises, which can be viewed as theoretically the most likely source of system failure. When engineers are trying to figure out the source of failure while being restricted by limit source in measurement field in reality, they can take new FMEA as reference and take these parts as priority in new measuring.

Assume we can take 16 measurements on solder joint resistance attached to different components to find the failure causes. Based on diagnosis result, we allocate measurements as inductors' and diodes' solder joint : 6 samples, capacitors' and resistors' solder joint : 2 samples.

Note that "one sample" means we heat up real boost converter at certain region to 90 degrees, keep other regions at 20 degree, take measurement on actual solder joint resistance, and test whether the system is functional or not with these resistance value through the circuit model again. Table 5.1 shows we rises temperature at resistor and take measurements on its solder joint resistance, note that here we assume all the other solder joints resistance remain at 0.0238, as ideal solder joint, since we do not have resource to take all the measurements.

Table 5.1: System output data with measurements (temperature rises at resistor)

System heat up at	Resistance of solder joint(Ω)	System output
Resistor	0.1026	Survival

After taking all measurements, we record all the system output data of failure and survival number and make list of all result as in Table 5.3.

Table 5.2: Analysis result with measurement data of boost converter

System heat up at	Number of measurement	Survival number	Failure number
Inductor	6	4	2
Diode	6	4	2
Capacitor	2	2	0
Resistor	2	2	0

Reliability estimation with data

Next step is to take Bayesian into reliability evaluation process. From Eq.3.16, the system survival number is r and failure number is $N-r$. Therefore, the system reliability function influence by four causes are:

Inductor: $Beta(r+1, N-r+1) = Beta(5,3)$

Diode: $Beta(5,3)$

Capacitor: $Beta(3,0)$

Resistor: $Beta(3,0)$

the reliability functions are shown in Fig.5.8.

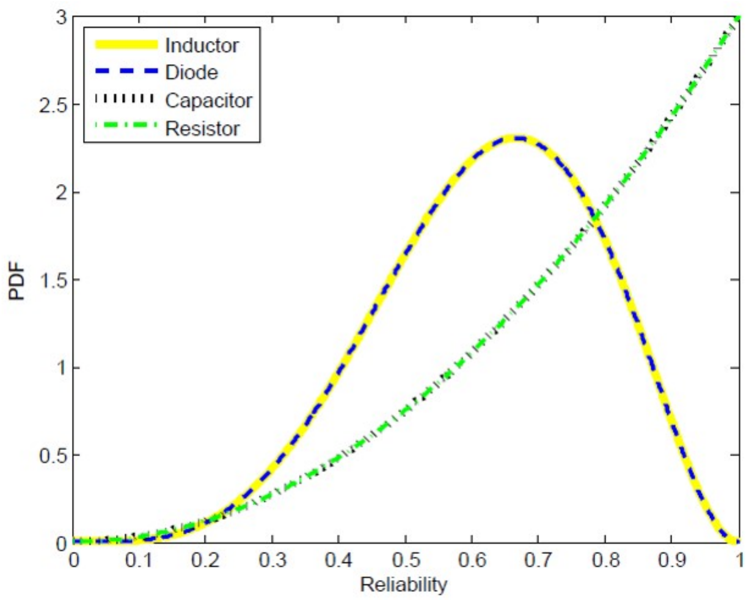

Figure 5.8: Reliability function with first round measurement

Adding measurement data and updating reliability

From the figure it can easily be seen that reliability functions of temperature rises at inductor and diode are the same. This means with current samples we can not tell which is the most critical source of failure. To construct a more specific rank and the most critical source, we have to add sample on these two regions. We add 4 more measurement on each of these two regions, the new list of system survival/failure number:

Table 5.3: Analysis result with more measurement data

System heat up at	Number of measurement	Survival number	Failure number
Inductor	10	6	4
Diode	10	7	3
Capacitor	2	2	0
Resistor	2	2	0

and reliability function can be obtained as: Inductor: $Beta(r+1, N-r+1) = Beta(7,5)$

Diode: $Beta(8,4)$

Capacitor: $Beta(3,0)$

Resistor: $Beta(3,0)$

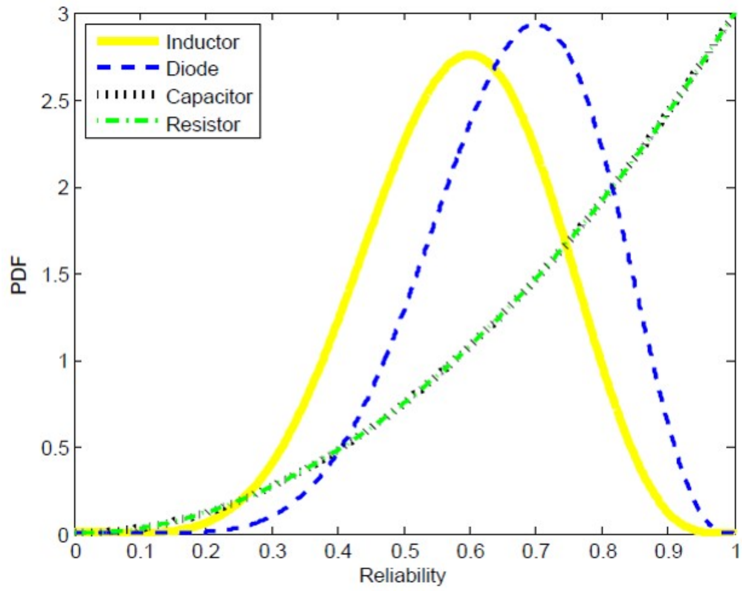

Figure 5.9: Reliability function with more data

Set reliability target at 0.7, the confidence range of each case would be: inductor $= 1 - \Phi_{beta}(0.7, 7, 5) = 0.2103$, diode $= 1 - \Phi_{beta}(0.7, 8, 4) = 0.4304$, and capacitor = resistor $= 1 - \Phi_{beta}(0.7, 3, 0) = 0.657$. Confidence range is the probability of reliability larger than target, the lower the CR the more likely for a system fail. Therefore the ranking of critical region is the same as the reverse ranking of CR: inductor > diode > capacitor = resistor. Which is the same ranking of that in original diagnosis result.

After diagnosing the critical region, we can make sure that the most critical part for boost converter is inductor, and the second worst part is diode. With this result we now know where to fixed to improve system reliability, which will be introduced in next sub-section.

5.1.2.5 Design alternatives for reliability improvement

The goal of diagnosis is to find the critical part of system, we can upgrade the system based on the result. Since we know which part is more severe to system reliability as temperature rises, we can increase the cooling system or re-arrange the component configuration to keep the critical region temperature as lower as possible.

For the boost converter, failure probability under original configuration is 0.535. Now we re-arrange components and test under same environment as Fig.5.10 shown, critical components, inductor and diode, are move to region with lower temperature as:

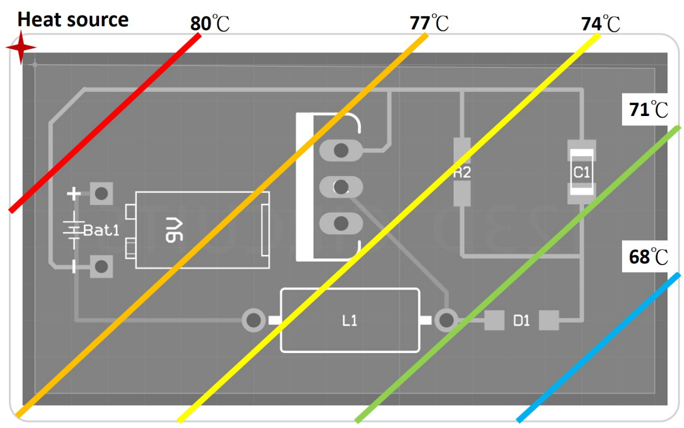

Figure 5.10: New configuration under same working environment

$$
\begin{aligned}
T_J(R) &= 73 + 77.1 \times 0.39 = 103.069 \\
T_J(C) &= 71 + 10.23 \times 0.13 = 72.32 \\
T_J(L) &= 72 + 75 \times 0.013 = 72.975 \\
T_J(D) &= 68 + 75 \times 0.15 = 79.25
\end{aligned}
\tag{5.4}
$$

Again we use ANSYS to simulate the real temperature gradient as Fig.5.11 and we can update the real temperature of each solder joint as Eq.5.5.

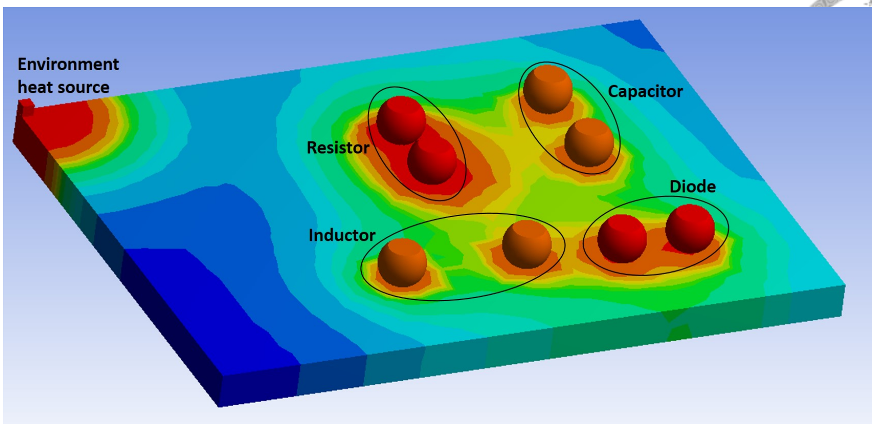

Figure 5.11: Temperature gradient analysis result of new layout

$$
\begin{aligned}
T_J(R) =& 104.158 \\
T_J(C) =& 75.33 \\
T_J(L) =& 74.472 \\
T_J(D) =& 80.116
\end{aligned} \tag{5.5}
$$

With temperature we can take them into Eq.4.1 to 4.5 again to obtain the resistance model. **After analyzing the failure probability is reduced to 0.396**, it is obvious that the failure probability can be reduced since the critical components are moved to a cooler region.

In this section, one of the failure mode in EV are analyzed through entire diagnosis method and the boost converter is improved to higher reliability. We will diagnose another failure item, the inverter, in the next section.

5.1.3 Failure due to inverter

Inverters, on the other hand, are electronic devices that change direct current (DC) to alternating current. Figure 5.12 shows the complete model of EV. This model develops a front-wheel drive EV using components from control and mechanical modeling domains. However in the case study we mainly focus on power electrical system - the inverter, as shown in Fig 5.13. An inverter like figure shown use control strategy, like vector control, and mechanical modeling to transfer DC input into three-phase electric power to E-motor.

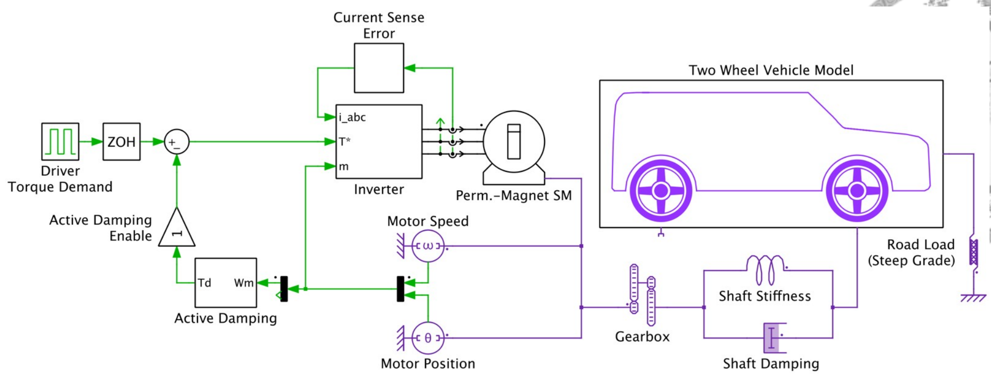

Figure 5.12: Entire model of electrical vehicle

Inverter has an important role in electrical vehicle, whether it is functional or not would influence the whole system directly [45]. In this case, we show how resistance in solder joint varied as temperature rise and then influent the function of inverter, and finally influent the velocity of entire vehicle.

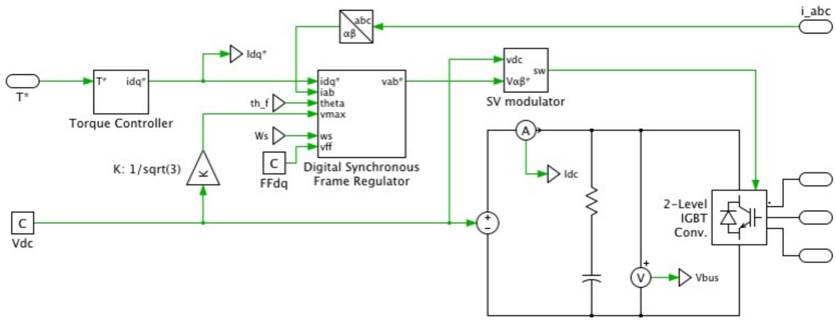

Figure 5.13: Sketch of power electrical system

Performance boundary

In this part we select the speed of EV as our standard in checking performance. Here we set our performance requirement as : electrical vehicle should be able to maintain speed larger than 3.27 km/hr.

$$Speed \geq 3.27(km/hr)$$

As the speed of vehicle drop lower than 3.27 km/hr we define the system fail, this model and performance requirement are used to demonstrate in the following diagnosis and analysis process.

5.1.3.1 Major causes of inverter failure

Figure 5.14 shows circuit of the inverter, first we try to find the most critical part of inverter from four parts, power source, resistor, capacitor, and insulated-gate bipolar transistor (IGBT).

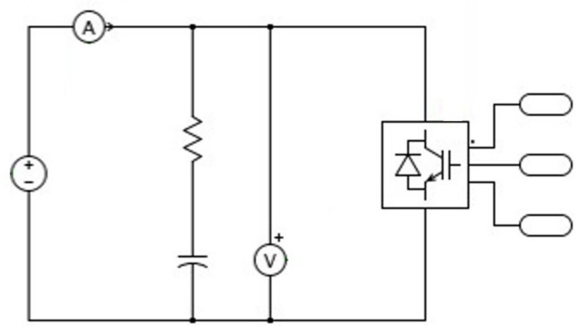

Figure 5.14: Circuit of inverter

After obtaining the circuit sketch, we add virtual resistor to circuit as Fig.5.15 shown. Where RS, RR, RC, and R_IGBT are the virtual resistor attach to (voltage) source, resistor, capacitor, and IGBT.

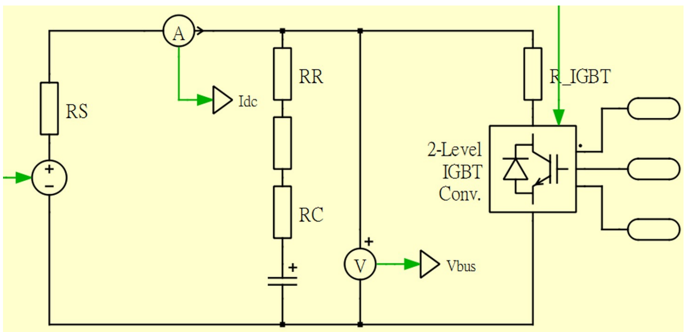

Figure 5.15: Inverter with virtual resistor

Again we construct resistance model and use batch mode incorporate PLECS into MATLAB to run Monte Carlo simulation with 1000 samples, then the diagnosis result of critical region as Fig.5.16 shows can be obtained.

From the diagnosis result, the most critical region of inverter is the IGBT and power source, both the solder joint of capacitor and resistor barely have influence on system as temperature rises.

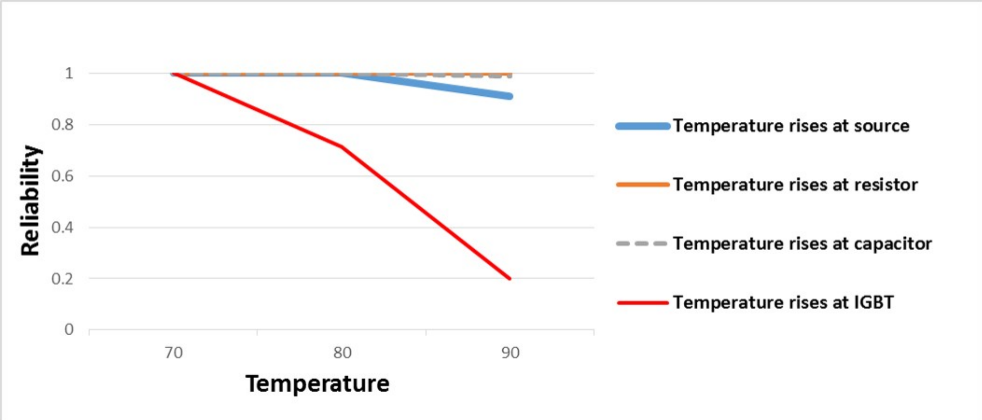

Figure 5.16: System reliability with temperature of different part rises

5.1.3.2 Probability of failure in an inverter

As for the probability of failure occurs, we first use original layout with given ambient temperature(Fig.5.17). Consider components heating derived from Eq.4.7 and parameters of components are in table5.4.

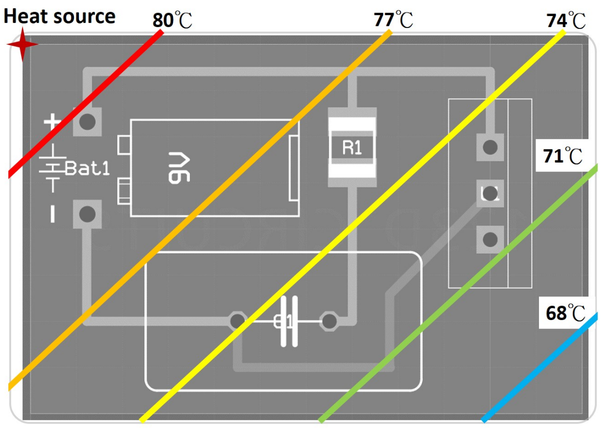

Figure 5.17: Original layout in ambient temperature

Table 5.4: Parameters of components

Region	Thermal resistance	Voltage(V)	Current(A)
Source	5	400	0.259
IGBT	4.86	400	0.249
Capacitor	10.23	400	0.01
Resistor	77.1	0.0001	0.01

the temperature of different solder joints after considering self heat are then derived as Eq.5.6.

$$
\begin{aligned}
T_J(Source) =& 80 + 5 \times 1.036 = 85.18 \\
T_J(IGBT) =& 71 + 4.86 \times 0.996 = 75.84 \\
T_J(C) =& 73 + 10.23 \times 0.04 = 73.4 \\
T_J(R) =& 74 + 77.1 \times 1e^{-8} = 74
\end{aligned}
\tag{5.6}
$$

Note that power dissipation of all components are 99%. With component temperature we can use ANSYS to obtain the temperature gradient of inverter and actual temperature of solder joint are:

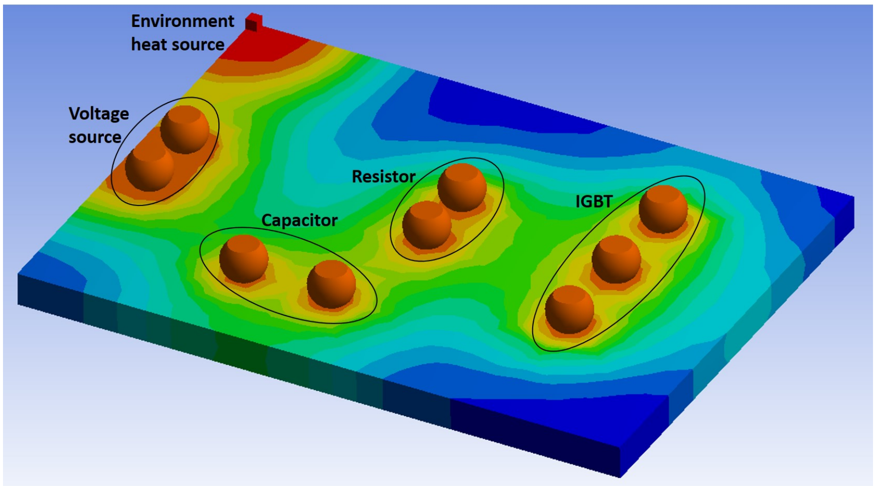

Figure 5.18: Temperature gradient analysis result of original layout (Inverter)

$$
\begin{aligned}
T_J(Source) =& 89.285 \\
T_J(IGBT) =& 76.49 \\
T_J(C) =& 73.428 \\
T_J(R) =& 74.017
\end{aligned}
\tag{5.7}
$$

With temperature we can construct every resistance model of solder joint in inverter and use Monte Carlo to evaluate system reliability. The probability of failure occurs is then 0.452.

This is the diagnosis process in analysis stage, after diagnosing we can obtain a modified FMEA chart for this failure mode as Fig.5.19

Ranking of critical region	Item/Function	Failure Mode	Effect(s) of Failure	Probability of failures occur	OCC	SEV	DET	RPN
IGBT>Source> Capacitor>Resistor	Inverter	Incorrect current leval	Vehicle stranded	0.452	4	8	4	128

Figure 5.19: modified FMEA of inverter

In the next section, we again use this modified FMEA to help us decide which part to sample first in measurement field under limited resource. The reliability assessment result can be updated via Bayesian to recheck the diagnosis result in analysis stage.

5.1.3.3 Subsequent measure-and-diagnose approach

From the modified FMEA, we can known the potential source(solder joint) of failure as temperature rises. In the measurement field we can take measurement based on this result of potential causes : **IGBT>source>capacitor>resistor**. Here we assume another situation that we have 15 failure inverters and we use another resource allocation strategy : at every new sample measurement we measure resistance at IGBT under certain temperature first, as system does fail(in analysis model) with this resistance, it is the end of this measurement on the first inverter, if not, we measure that of voltage source next, again as system fails we stop the measurement on this inverter or take measure at capacitor when system survive. Use this strategy under limit of 15 inverters, we can obtain the measurement data as table5.5 shown. Note that with this strategy we totally take 15+11+9+9=44 samples.

Table 5.5: Analysis result with measurement data of inverter

System heat up at	Number of measurement	Survival number	Failure number
IGBT	16	11	5
Source	11	9	2
Capacitor	9	9	0
Resistor	9	9	0

After taking measurements we can obtain reliability function and confident range(reliability target=0.7) as:

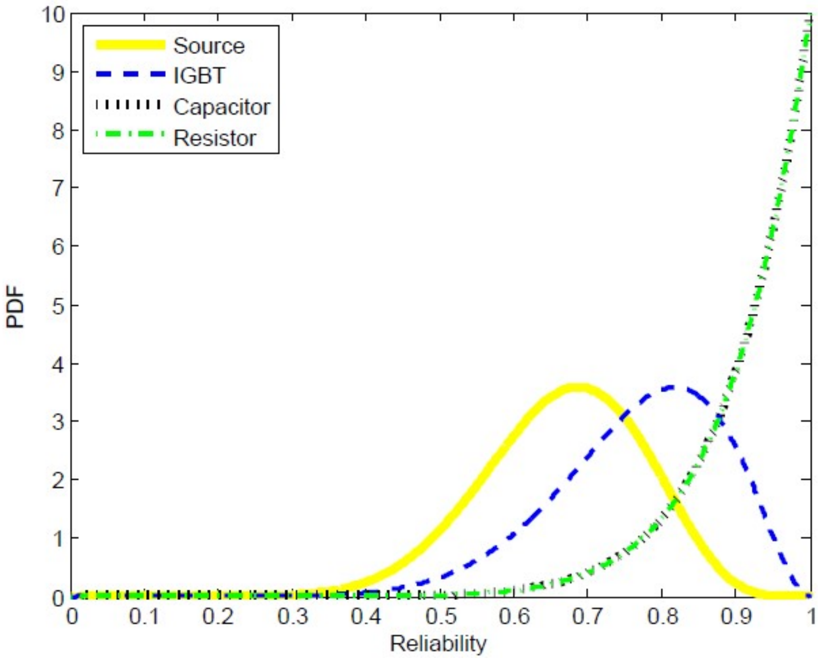

Figure 5.20: Reliability functions

$$
\begin{aligned}
CR_{IGBT} &= 0.5501 \\
CR_{Source} &= 0.7472 \\
CR_{Capacitor} &= 0.9718 \\
CR_{Resistor} &= 0.9718
\end{aligned}
\tag{5.8}
$$

With real measurement data, we can recheck the diagnosis results at analysis stage. In the next step, we will use diagnosis result to design a higher reliability system.

5.1.3.4 Design alternatives for reliability improvement

The probability of failure occurs for the original system is 0.435. From the diagnosis result we know that the critical part are IGBT and voltage source, in new design we try two ways to improvement system reliability, or decrease the probability of failure occurs : **change the configuration of system** and **refine the quality of solder joint**. The new layout is shown in Fig.5.21, and the temperature of different components are:

$$
\begin{aligned}
T_J(Source) &= 74 + 5 \times 1.036 = 79.18 \\
T_J(IGBT) &= 68 + 4.86 \times 0.996 = 72.84 \\
T_J(C) &= 79 + 10.23 \times 0.04 = 79.4 \\
T_J(R) &= 74 + 77.1 \times 1e^{-8} = 74
\end{aligned}
\tag{5.9}
$$

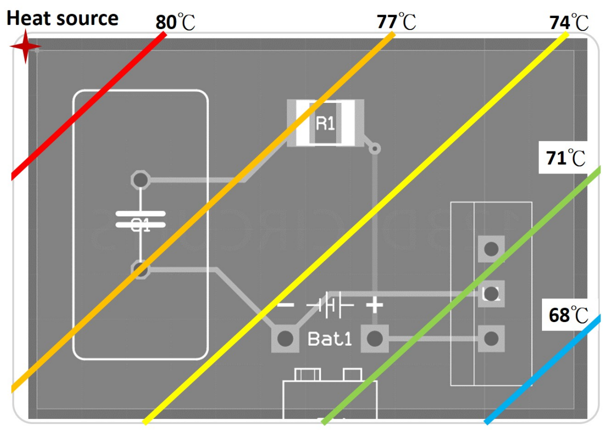

Figure 5.21: New layout of inverter in same ambient temperature

Next we take these temperature into ANSYS and get the real temperature gradient as:

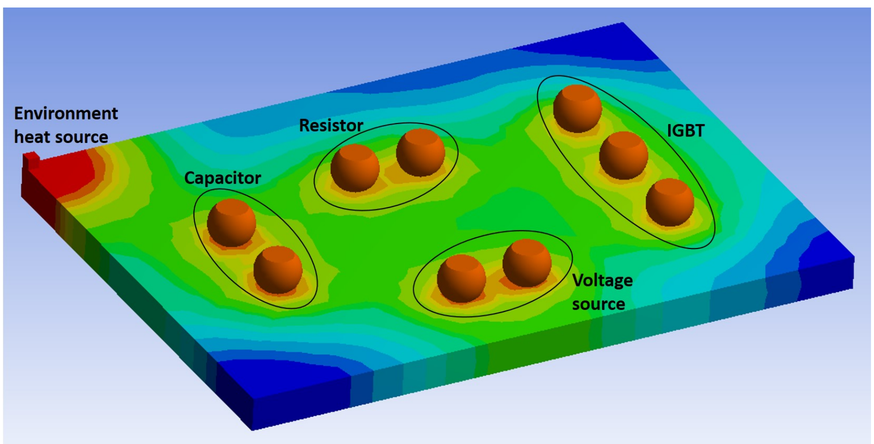

Figure 5.22: Temperature gradient analysis result of original layout (Inverter)

$$
\begin{aligned}
T_J(Source) &= 79.254 \\
T_J(IGBT) &= 73.859 \\
T_J(C) &= 79.468 \\
T_J(R) &= 74.036
\end{aligned}
\tag{5.10}
$$

After rearrange components the probability of failure can be reduced a lot to 0.024. As for refining the solder joint, we assume that the production uncertainty is reduced by higher accuracy, that is, the variation in resistance model is reduced to 0.002(original is 0.00375). **By refining solder joint the probability of failure occurs can be reduced to 0.32**.

From this section, part of inverter is used to show the impact of small change in solder joints on a complex system. The concept of this diagnosis method is that although all the components in system are functional, system may still fail due to small performance deviation in solder joints. In this case study, the temperature sensitive part in inverter are found, with the diagnosis result we can re-exam our design and make improvement toward higher reliability.

5.1.4 Diagnosis result

From last two sections, the entire modified FMEA chart can be fulfilled as Fig.5.23. From this modified FMEA chart we can find out although the original number of failure probability(OCC) are the same (both are 4), the actual failure probability of two item may still be different from each other. This result shows another capability of proposed method that can help us find the more possible failure mode for same symptom. With this modification on FMEA, engineers can finally get information of where or which item to measure or fix first. Furthermore, with information of ranking of critical region, engineers can know how to modify or redesign the failure item for higher reliability under high temperature.

Ranking of critical region	Item/Function	Failure Mode	Effect(s) of Failure	Probability of failures occur	OCC	SEV	DET	RPN
Inductor>Diode> Capacitor>Resistor	Boost converter	Incorrect Voltage Level	Vehicle broke down	0.557	4	8	6	192
IGBT>Source> Capacitor>Resistor	Inverter	Incorrect current leval	Vehicle broke down	0.452	4	8	4	128

Figure 5.23: Modified FMEA chart

5.2 Diagnosis of high reliability system

5.2.1 Diagnosis process in analysis stage

In this case we use the same model, boost converter, but adjust the performance boundary to show the possible problem that the method would faced. Note that in this case we only try to find the most possible cause of failure. The failure mode is same as previous case, incorrect voltage level from boost converter, but we change the performance boundary as:

$$Voltage \geq 18.05(V)$$

with this new performance boundary and construct complete solder joint resistance model, we can obtain the analysis result of critical components as: from the figure we can see

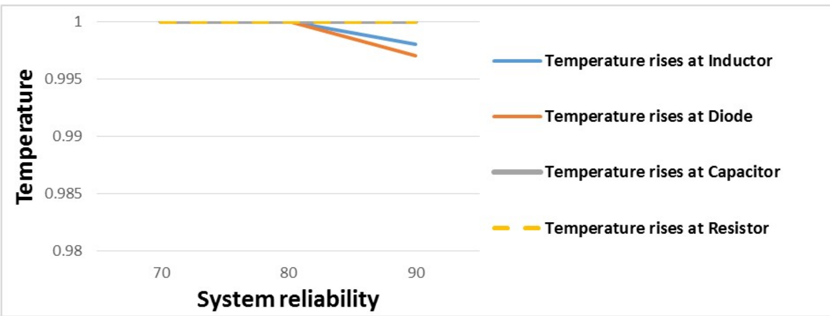

Figure 5.24: System reliability as temperature of different parts rise

that four possible causes barely have influence on system reliability, the most possible cause is temperature rises at diode which would however only make system reliability drop 0.003. In this analysis stage we can only make conservative statement that the relative possible causes are temperature rises at diode and inductor. This result would be used in measurement field to decide where to put more resource on.

5.2.2 Diagnosis and reliability update in measurement field

In this case we only take measurements on solder joint resistance of inductor and diode since other two regions will not influence system reliability. We first take 10 samples on each region and test whether system is functional or not with these data, the analysis result with these data is shown in Table 5.7 and reliability functions are shown in Fig.5.25.

Table 5.6: Analysis result with measurement data

System heat up at	Number of measurement	Survival number	Failure number
Inductor	10	10	0
Diode	10	10	0

From the figure we can see two reliability functions are same, as previous chapter men-

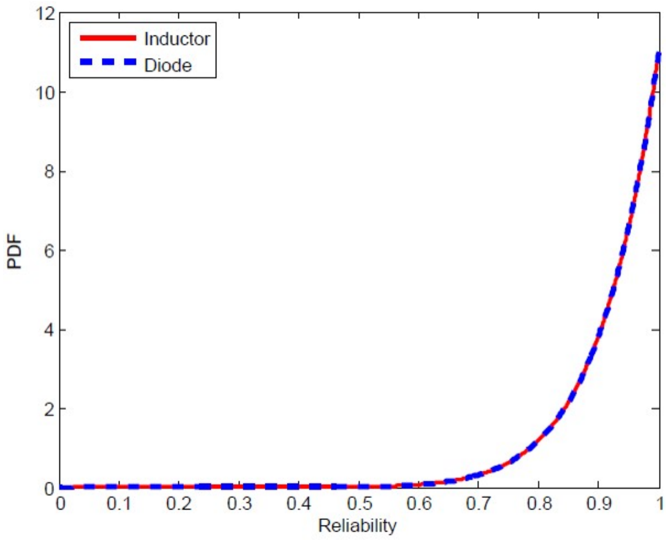

Figure 5.25: Reliability function of different causes in case 2

tioned, same reliability functions will lead to same confident range which will make diagnosis result infeasible. Therefore, to make complete diagnosis result we have to add on both possible causes. We add 20 samples this time and obtain the update table of system output data as: from the table we find that we still have same output data on two possible causes, which represents same parameters in reliability function, survival number r and fail number $N - r$, that still make reliability functions and confident range the same.

Table 5.7: Analysis result with more measurement data

System heat up at	Number of measurement	Survival number	Failure number
Inductor	10	30	0
Diode	10	30	0

In this case we find that we can almost not be able to complete the diagnosis process in measurement field due to **we can hardly measure a 'failure' sample in a high reliability system which would make reliability assessment via Bayesian fail**. In this case, system reliability is remain 0.997 and 0.995 after considering the influence of solder joints of inductor and diode, respectively. Therefore, it is very difficult for us to measure a 'fail' sample with only 30 samples, to make complete diagnosis result we should probably take up to hundreds of measurement which is almost impossible as mentioned in previous chapter. Therefore our method would meet this bottleneck when dealing with high reliability problem.

5.3 Summary

The first case study shows the ability of the proposed method that can:

- diagnose electrical system from aspect of physics of failure, which can reveal environment uncertainty on the system or the cause of failure even none components in system is failure.
- give suggestions on new measurements under limited resource in measurement field, also the reliability updated scheme through limited measurement data are constructed and can be use to recheck the result of analysis result.
- give recommendations on modifying system for higher reliability.

Furthermore, in case 2 the restrict of proposed method are shown since we can barely obtain any 'failure' data with few measurement under high reliability problem, therefore we can almost not be able to make diagnosis result based on these data since all measurement of possible causes lead to 100% system reliability.

Chapter 6

Conclusion and Future Work

6.1 Conclusion remark

The main purpose of this thesis is to propose a diagnosis method for electrical systems. From the diagnosis result engineers in measurement field can obtain suggestion on new measurement under limited resource. Also the reliability evaluation through few samples can be accomplished through Bayesian inference. Finally engineers can re-design a system with higher reliability.

Main contributions of this thesis:

1. **New diagnosis method for electrical system:** This thesis proposes a diagnosis method for electrical system from aspect of physics of failure. The method can foresee the influence of environment uncertainty on system in the early design stage.

2. **Suggestion on new measurement for detecting failure:** In reality measurement field, we only have limited resource and have to determine where to measure to obtain the real failure source. The diagnosis result can provide the highest potential cause and give suggestions when new measurements are needed.

3. **Assess reliability through few measurement data:** The real measurement data we can obtain in reality is few and we usually have to evaluate system reliability through these data. A Bayesian based assessment method is established to solve this problem.

6.2 Future work

The thesis still have some points to be done to make method more practical:

- **Consider time dependent problem:** In this thesis we only consider time independent problem, while in reality solder joints may deteriorate or crack as exposing to severe environment for a long time. Also the Bayesian inference should be able to update the reliability function in time independent problems. With consideration time dependent problem, we can extend our diagnosis method to **prognosis** method.

- **Take failure of components and solder joint into account:** In this work we only consider the deviation of solder joints resistance, while components may fail and solder joint may generate crack that also influent system reliability.

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