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Reliability Study of Electric Vehicle Drive Motor Control System

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Abstract: *This paper focuses on the study of the reliability of the control system for electric vehicle drive motors. The methods employed include fault tree analysis, failure mode and effects analysis, typical fault mode analysis, and Bayesian uncertainty inference. Firstly, typical fault mode analysis was used to thoroughly understand the causes and characteristics of the faults and to predict and evaluate the fault modes. Secondly, a fault tree for the control system of the drive motor was constructed and FMEA analysis was carried out, identifying the potential impact and failure causes of various fault modes. Finally, Bayesian networks were used to infer the potential fault probability of the controller, providing scientific basis and support for the fault diagnosis system, and reducing maintenance and repair costs. The methods used in this paper can provide reference for the reliability research of electric vehicles.*

Keywords: *electric vehicle, drive control system, reliability, Bayesian network, FMEA, fault tree*

1. Introduction

With the popularization of electric vehicles and the intensification of market competition, vehicle reliability has become a focus of consumer attention, and the application of reliability engineering in the field of electric vehicles is increasingly valued. As early as the 1950s, reliability engineering began to be widely used in the military industry, and a series of reliability standards were developed, such as MIL-STD-785 and MIL-STD-781. The automotive industry is one of the industries where reliability standards are applied more widely, and various countries have developed a series of automotive industry standards, such as SAE J1739 in the United States and ISO 26262 in Europe.

Research on the reliability of electric vehicles mainly focuses on battery systems, drive control systems, body structure, and charging systems. Battery system research includes battery cell and system failure rates, as well as battery life prediction. Drive control system research includes motor, inverter, and control system failure rates. Body structure research includes fatigue life, stiffness, and strength. Charging system research includes failure rates of charging piles, cables, and plugs. Due to the complexity of electric vehicle systems and the increase of uncertainty factors affecting their reliability, such as temperature, humidity, electromagnetic interference, vibration, maintenance errors, wear, aging, design, and manufacturing, uncertain failures may occur[1]. While fault decoders have limitations, Bayesian networks can provide a flexible method to infer potential faults and estimate probabilities based on known information[2-3]. Thus, Bayesian networks can help researchers understand the fault characteristics and behaviors of electric vehicle systems and improve their reliability and safety.

2. Reliability Analysis of Electric Vehicle Drive Motor Control System

2.1. Failure Mode and Effects Analysis (FMEA)

The failure mode and effects analysis (FMEA) adopts the inductive analysis method to analyze the failure effects of various components and electronic components of the system, as well as the causes of

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failures, to provide reference for the next step of fault detection and improve the system's reliability. Figure 1 shows the FMEA analysis process.

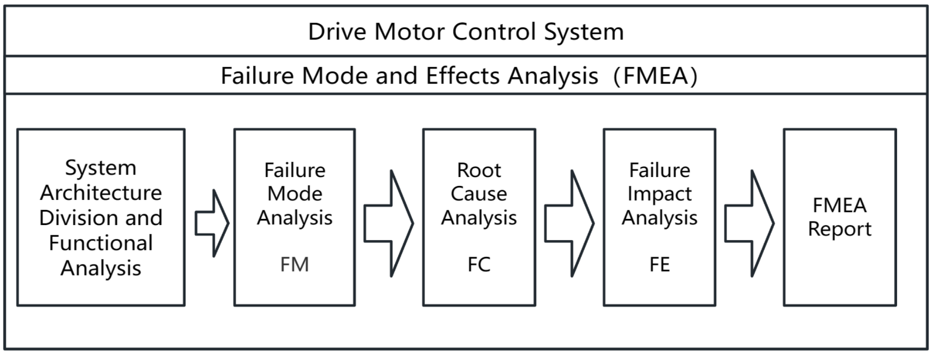

Figure 1: FMEA analysis process.

To ensure the reliability of electric vehicles, the high-voltage system should be protected from overloading, short circuits, and overvoltage breakdowns. Additionally, electromagnetic interference (EMI) is a critical factor that should be considered when analyzing failure modes. EMI faults may include motor noise interference and signal interference, which can affect electronic components like chips, sensors, and signal transmission systems. If EMI levels exceed certain thresholds, they can lead to transmission errors or failure. FMEA should be used to analyze different fault causes and symptoms in detail when dealing with uncertain factors, and corresponding elimination plans should be formulated. The figure 2 below depicts three typical failure modes of electric vehicles.

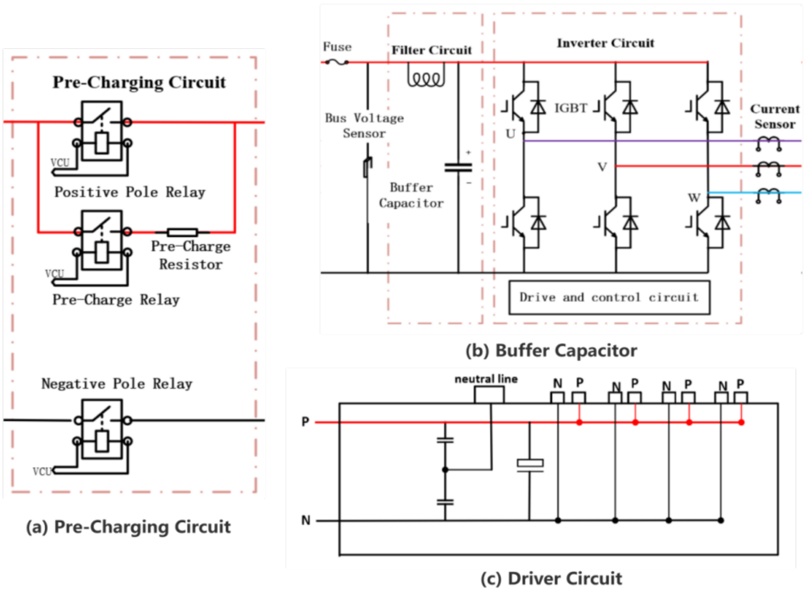

Figure 2: Fault case analysis.

The pre-charge circuit topology is shown in Figure 2(a), which is a protective control switch that manages the charging and discharging of the power battery to the drive motor control system in an electric vehicle. A pre-charge control is designed in high-voltage electric vehicle systems to prevent damage to high-voltage circuits and components due to instantaneous large currents during high-voltage power-on. The pre-charge contactor is closed first, and the current is limited by the pre-charge resistor to pre-charge the bus capacitor before outputting high-voltage power to the outside. If the pre-charge fails, the system will not close the positive contactor, so special attention should be paid to the pre-charge state during failure mode analysis.

Figure 2(b) displays the inverter circuit topology, which mainly comprises IGBT modules, buffer capacitors, bus current sensors, and other components. The main failure modes include IGBT open circuit, short circuit, buffer capacitor open circuit, short circuit, aging, and bus current sensor parameter drift. The short circuit failure of the IGBT module has the most severe impact on the drive motor control system, leading to bus over-current faults and the generation of braking torque in the drive

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motor.

Figure 2 (c) illustrates the buffer capacitor topology. The open circuit and short circuit faults of the buffer capacitor in an electric vehicle are also significant. The buffer capacitor works in harsh environments of charging and discharging, over-voltage, and high temperature, which leads to performance degradation such as decreased capacitance, material aging, and increased impedance. Serious aging phenomena can affect the electric vehicle's reliability and cause safety accidents. The table 1 below analyzes the failure mode and effects of each module in the drive motor control system.

Table 1: Failure mode analysis of the drive motor control system.

Fault mode	Fault cause	Fault impact
Electromagnetic interference (EMI) failure	The power devices and motor in the controller produce strong electromagnetic radiation and noise, which may cause interference with surrounding electronic equipment when it exceeds a certain level.	Electromagnetic fields leaking into the surrounding environment may cause interference to other electronic devices, such as car instruments and communication equipment.
Contact welding	Overvoltage and overcurrent can cause the contacts to weld or stick together, making them unable to separate.	It may cause circuit short circuit or overload, and damage core components such as batteries and electric motors.
Contactors bounce	The internal contacts may suffer from oxidation, deformation, or corrosion, leading to poor contact.	The circuit is unable to work properly or works unstably.
Burnout of contactors	Overload, overheating, and arcing can cause internal burning or short circuit in the contactor.	Causes damage to the electric vehicle circuit or burns out equipment.
Buffer capacitor failure.	Parameter out-of-tolerance, performance degradation, aging.	This could cause the electric vehicle's charging system to fail to start normally, potentially affecting the normal operation of the electrical system.
IGBT short circuit	Faulty IGBT switches can lead to direct short circuits in bridge arms, internal branch short circuits affecting the normal operation of the circuit, or output short circuits between pins causing excessive current, overheating and burning.	Unable to control the on-off of the IGBT bridge arm, the motor cannot work properly, the motor speed cannot be adjusted or directly stopped, resulting in circuit overload, abnormal voltage, and temperature rise.
IGBT overvoltage	The collector-emitter overvoltage of IGBT is caused by factors such as excessive bus current, abnormal control signals, etc. The gate-emitter overvoltage is caused by abnormal gate drive circuits and electrostatic discharge.	If the voltage in the circuit exceeds the rated voltage of the IGBT, it may cause breakdown or burnout of the IGBT, resulting in the entire system not working properly.
IGBT over-temperature	Insufficient IGBT cooling capacity may result in an increase in the temperature of the IGBT housing.	This can lead to a shortened IGBT lifespan, reduced driving power for the motor, and may even result in a circuit short-circuit.
Power Module Failure	The power supply module can fail due to internal component damage caused by overvoltage, overload, or overheating. Loose connections in the connectors can also result in poor contact and failure of the switching power supply.	It can cause damage to the power module and fail to provide stable power to the drive control circuit, which affects the driving safety and performance of electric vehicles.

2.2. Fault Tree Analysis

FTA (Fault Tree Analysis) is a logical reliability analysis method that models the causes of system failures and analyzes their probabilities and impacts[4]. It uses logical symbols to diagram the system's failures and internal component failures, creating a fault tree with a causal relationship between the top event (system failure) and the bottom event (sub-component failure) , as shown in Figure 3 and Figure 4.

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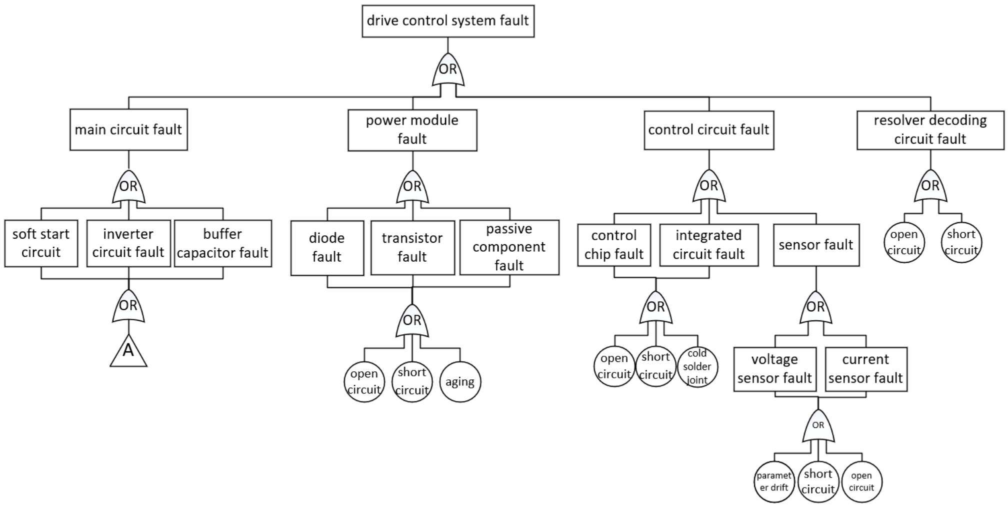

Figure 3: Fault Tree Analysis.

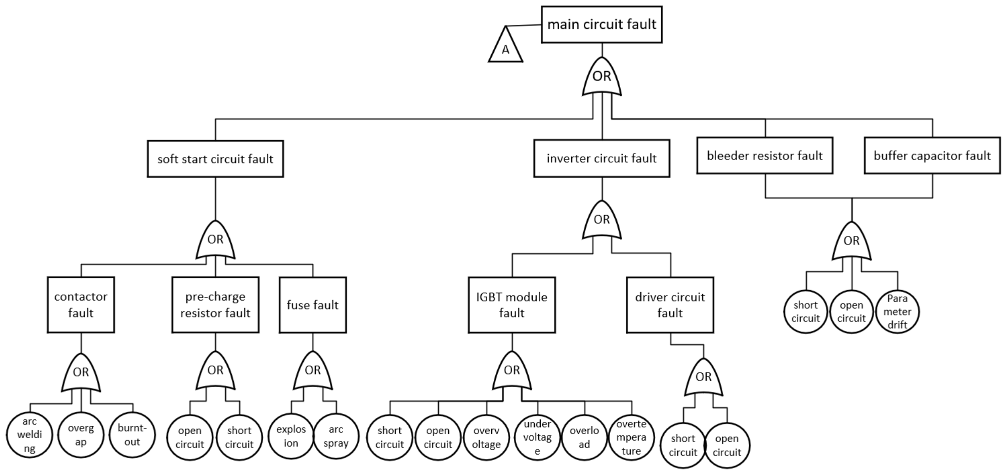

Figure 4: Fault Tree Analysis.

3. Calculation of Failure Model for Drive Motor Control System

Failure rate model is an important parameter in reliability analysis. When considering the reliability analysis of complex systems, the drive control system is viewed as a whole. Based on the various failure modes that may cause system failure analyzed in the system fault tree, a top-down analysis is conducted to determine the direct causes of the top-level event. According to the GJBZ 299C-2006 reliability prediction standard, factors affecting the failure rate of electronic components include the type of components, usage environment, normal operating temperature, product quality, etc. The quality coefficient is based on the GB/T quality assessment level, and all components are designed to be B-class standards.

The working failure rate model of the control circuit for the drive motor control system:

$$\lambda_p = \lambda_b\ \pi_E \pi_Q \pi_L \pi_T$$

λ_b—basic failure rate, λ_p—operational failure rate, π_E—environmental factor, π_Q—quality coefficient, π_L—maturity factor, π_T—temperature stress factor.

Basic failure rate: $\lambda_b = A_S\lambda_C + \lambda_{RT}N_{RT} + \sum \lambda_{DC} N_{DC} + \lambda_{SF}$

$A_S\lambda_C$—substrate area and complexity, $\lambda_{RT}N_{RT}$—total failure rate of thin film resistors, $\sum \lambda_{DC} N_{DC}$—external component failure rate, λ_{SF}—process failure rate.

Establish a data table 2 for component node numbering and failure rate data, using the control circuit failure rate as an example.

Table 2: Failure rate modeling analysis

Component name	Quantity	mathematical models	Failure rate(10^{-6}/h)
REF3020AIDBZ,SPX1117M3-L/TR etc	19	$\lambda_p=\pi_Q[C_1\pi_1\pi_V+(C_2+C_3)\pi_E]\pi_L$	5.8
Resistor etc	175	$\lambda_p=\lambda_b\ \pi_E\pi_Q\pi_R$	6.125
Polarized Capacitor etc	198	$\lambda_p=\lambda_b\ \pi_E\pi_Q\pi_{CV}\pi_{ch}$	7.92
Inductor	16	$\lambda_p=\lambda_b\ \pi_E\pi_Q\pi_K$	0.144
Zener Diode/Default Diode etc	6	$\lambda_p=\lambda_b\ \pi_E\pi_Q\pi_r\pi_A\pi_{S2}\pi_c$	0.6
Total			20.598

4. Building and optimizing Bayesian networks

4.1. Bayesian Network Construction and Optimization

Bayesian Network (BN) is a graphical model used to construct probabilistic graphical models, which is a method for describing the probabilistic relationships between variables. It is a probability model based on Bayesian theorem, also known as Belief Network or Directed Acyclic Graph (DAG) model.

$$P(A|B)=P(B|A)*P(A)/P(B)$$

P (A|B) represents the probability of event A occurring given that event B has occurred. P(B|A) represents the probability of event B occurring given that event A has occurred. P(A) and P(B) represent the probabilities of events A and B occurring, respectively. P(A) and P(B) are known as prior probabilities, while P(A|B) is known as posterior probability.

Suppose there are n nodes, and the state of the i-th node is X_i, i=1,2,...,n. Let T be an event such that if T occurs, the state of the i-th node is X_i, otherwise it is X_i. We can use the following formula to represent the probabilistic relationships between nodes:

$$P(X_1,X_2\cdots X_n,|T)=P(X_1|T)*P(X_2|X_1,T)*\cdots*P(X_n|X_1,X_2,\cdots T)$$

4.2. Optimization of Bayesian Networks based on Fault Tree

The electric vehicle drive motor control system requires a car decoder for diagnosis when a failure occurs. However, relying solely on fault codes for diagnosis may lead to inaccurate results due to the close relationship between the motor control system and other components. Bayesian networks are important in reliability analysis as they offer a flexible and effective probabilistic inference method to analyze and predict system reliability and failure rates. Combining fault trees and Bayesian networks can improve the accuracy and efficiency of fault analysis and diagnosis. This involves converting events in the fault tree into nodes in the Bayesian network, establishing the Bayesian network structure based on the relationships between the events, and using the Bayesian network's inference algorithm for fault analysis and diagnosis, as shown in Figure 5.

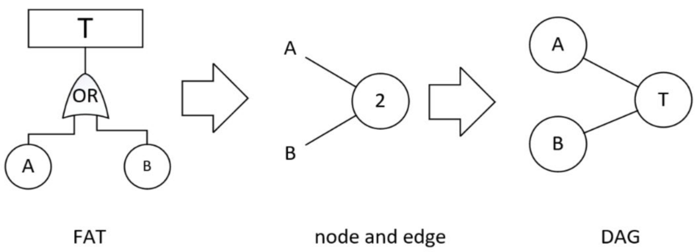

Figure 5: Generating DAG Model from Fault Tree

The steps for establishing a fault Bayesian network from a fault tree are as follows: Assume there is a fault tree consisting of N events, where the occurrence of event i is represented by 0/1, and each basic event in the fault tree corresponds to a root node in the network. Based on the hierarchical relationship of the fault tree, establish a directed acyclic graph fault diagram to determine the order and relationship of the nodes. Determine the conditional probability distribution CPT table for all nodes.

Each node attribute of the Bayesian network is set with two parameters: false and true. Based on the established failure rate model, the conditional probability distribution (CPD) table 3 of the Bayesian network can be obtained.

Table 3: Failure rate modeling analysis

Node name	type	value	CPD
IGBT	discrete	{0, 1}	1-0.000008, 0.000008
driver_circuit	discrete	{0, 1}	1-0.000009, 0.000009
inverter_circuit	discrete	{0, 1}	IGBT=0, driver_circuit=0: 1-0.000017, IGBT=0, driver_circuit=1: 0.000008, IGBT=1, driver_circuit=0: 0.000009, IGBT=1, driver_circuit=1: 1-0.000008

4.3. Bayesian network operation conclusion and analysis

Bayesian network inference is an effective tool for analyzing uncertain information and making decisions in a system. It learns a reasonable network structure from data using a pre-specified conditional probability distribution and infers the probability of an event given known evidence. The variable elimination method is a common uncertainty inference algorithm used in this article for fault diagnosis of the drive motor system. It eliminates random variables one by one to reduce computational complexity and obtain the probability distribution of the target variable. The advantages of this method include efficient processing of large-scale probability networks, avoiding exhaustive computation, improving model accuracy and robustness by avoiding the independence assumption in local probability models, and supporting prior knowledge and evidence to accurately calculate probability distributions.The following figure 6 shows that when a potential fault occurs in the system circuit, it will have a potential impact on the motor control system, resulting in a fault probability of 0.5.

```
+--------------------+-------------------------+
| motor_controller   |   phi(motor_controller) |
+====================+=========================+
| motor_controller_0 |                  0.5000 |
+--------------------+-------------------------+
| motor_controller_1 |                  0.5000 |
```

Figure 6: Result diagram of using variable elimination algorithm.

5. Conclusions

This paper comprehensively studied and analyzed the reliability of the motor control system using methods such as fault tree analysis, failure mode and effects analysis, typical failure mode analysis, and Bayesian uncertainty inference. The fault tree and FMEA analysis provided a systematic analysis approach for understanding various potential faults and their impact on the electric vehicle's motor control system. Typical failure mode analysis helped to better predict and evaluate the controller's failure modes by understanding their causes and characteristics. Lastly, Bayesian uncertainty inference provided a precise estimation and prediction of the controller's failure probability, supporting scientific decision-making for maintenance and repair of the system and lowering associated costs.

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