Reliability Analysis on Truck Based on Weibull Distribution

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Abstract. The article addresses the shortcomings in reliability analysis and modeling between various subsystems in a certain type of truck. By organizing and analyzing the failure data of each subsystem, the reliability modeling of the entire vehicle and its subsystems is established based on the Weibull distribution. After that, using hypothesis tests: linear correlation coefficient tests and D-tests to evaluate the parameter estimation structure. Additionally, the paper discusses the importance of each subsystem within the overall vehicle model and conducts failure analysis and failure classification evaluation. The reliability analysis of this truck reveals that, in terms of importance, the frame has the greatest impact on the overall vehicle reliability. In terms of failure analysis, the clutch and the reducer present a higher degree of failure hazard to the vehicle system. The findings of this paper provide essential research methods and references for subsequent discussions and analyses of this type of truck.

Keywords: Reliability modeling; Weibull distribution; failure severity assessment; failure analysis.

1. Introduction

In recent years, the production and sales of domestic automobiles have significantly increased year by year, leading to a further increase in market share for domestic brands. Reliability analysis of automobiles has always been one of the key focuses in the research of automotive quality engineering. The evaluation of operational reliability involves determining the reliability of vehicles (including assemblies and systems) during actual use. This evaluation and failure analysis can reveal the weakness with lower reliability. Based on reliability evaluation and analysis, effective improvements can be proposed, allowing for the implementation of effective measures. Therefore, reliability evaluation is fundamental to improving reliability, as well as laying the groundwork for research on vehicle maintenance support and decision-making. There is a substantial body of literature in the field of reliability. Braglia M [1] using a multivariate statistical approach to classify mechanical components under different working condition using MTBF; Chenhao Wang [2]analyzed the reliability of commercial vehicle engines using neural networks and data from similar products; Mohamed A[3] implementing MTBF, MTTR, and Reliability to analyze the critical autonomous mechanical machine in a beer plant to increase the working stability and efficiency of the plant; Sihang Yang, Zhuowei Liu[4],[5]applied the fuzzy fault tree method to conduct reliability analysis of automotive subsystems; Ahshan R [6] apply MTBF by using algorithmic computation on a solar array to check the array's working reliability and analyze the possible cause of the failure; Chenxi Zhou, Shuaijun Fang[7],[8]discussed decision-making analysis and disposal methods related to automotive maintenance and faults; Zheng Ma[9]conducted reliability modeling of electric vehicle subsystem models using a model-driven structural analysis approach; Tieling Meng[10] discussed the mean time between failures (MTBF) and the average failure rate function for a certain type of vehicle; I.M. Ribeiro[11], Pooya Alavian[12], and Fan C. Meng[13] analyzed and evaluated the overall availability of mechanical systems and possible improvement methods by discussing the system's average failure mileage (MTBF).

Current research on automotive reliability mainly focuses on analyzing the stress effects on critical components and the lifespan of crucial parts. Generally, current reliability analyses focus on several specific vulnerable parts of a vehicle, instead of considering the total vehicle system and its subsystems to discuss potential failure and their impacts during operation process.

To address the issues mentioned in the last paragraph, this paper will analyze and establish the model from not only the total vehicle system but also from every single subsystem, including vehicle frame (VF), Electromagnetic switch (ES), transmission shaft (TS), transmission case (TC), Braking system (BS), mid and rear axles (MR), clutch system (CS), Propelling Rod(PR). This paper establishes a reliability model based on the Weibull distribution; conducts a d-test to ensure every model follows the Weibull distribution; analyzes every subsystem importunate, conducts failure analysis and graded evaluation to each subsystem respectively.

2. Establishment of truck reliability model

This paper collecting 231 failure mileage data points for this vehicle from 8 subsystems by tracking the usage of a specific type of truck during a given period of time. The collected data has been organized and sorted, as detailed in Table 1.

Table 1. The vehicle (V) failure mileage data.

i	t_i	i	t_i	i	t_i
1	10	10	40	19	110
2	10	11	40	20	110
3	10	12	40	21	130
4	10	13	50	22	140
5	10	14	50	23	140
6	10	15	70	24	150
7	20	16	70	……	……
8	20	17	80	230	14110
9	30	18	90	231	14200

2.1. Establishment of reliability model for Vehicle (V)

Firstly, a vehicle reliability model is constructed by using collected failure data points as Table 1 shows, to model the overall vehicle reliability.

2.1.1. Perimeter estimation in reliability model

Generally, assuming the automobile reliability model follows Weibull distribution. Therefore, this section provides a detailed explanation of the least squares parameter estimation process for the Weibull distribution. For n sample points (x_i, y_i) i =1, 2… n. Take $l_{xx} = \sum_{i=1}^{n} x_i^2 - n\bar{x}^2$ $l_{yy} = \sum_{i=1}^{n} y_i^2 - n\bar{y}^2$ $l_{xy} = l_{yx} = \sum_{i=1}^{n} x_i y_i - n\bar{x} \times \bar{y}$, $\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$ $\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$

The regression model is given by:

$$y = A + Bx + \varepsilon \tag{1}$$

In the equation: a, b - regression coefficient

ε - Deviation

The corresponding least squares constraint criterion is:

$$Q_y = \sum_{i=1}^{n} \varepsilon_i^2 = \sum_{i=1}^{n} (y_i - a - bx_i)^2 = \min \tag{2}$$

In the equation: Q_y - Sum of Squares of Deviations

ε_i - The deviation of the i-th sample point

When the partial derivative of Q_y with respect to *a* is equal to 0, and the partial derivative of Q_y with respect to *b* is also equal to 0, Q_y reaches its minimum value. Correspondingly, the estimated values of the parameters *a* and *b* can be obtained as:

$$\hat{a} = \bar{y} - \hat{b}\bar{x} \tag{3}$$

$$\hat{b} = \frac{l_{xy}}{l_{xx}} \tag{4}$$

Two parameter Weibull distribution function is:

$$F(t) = 1 - \exp[-(\frac{t}{\alpha})^{\beta}], \qquad t \geq 0 \tag{5}$$

In the equation, α -scale parameter $\alpha \geq 0$

β -shape parameter $\beta \geq 0$

Reliability function is:

$$R(t) = \exp[-(\frac{t}{\alpha})^{\beta}], \ t \geq 0 \tag{6}$$

Failure rate function is:

$$\lambda(t) = \frac{\beta}{\alpha}(\frac{t}{\alpha})^{\beta-1}, \ t \geq 0 \tag{7}$$

Taking the natural logarithm twice on equation (5) and transforming it linearly:

$$\ln\ln\frac{1}{1-F(t)} = -\beta\ln\alpha + \beta\ln t \tag{8}$$

Let $y_i = \ln\ln\frac{1}{1-F(t_i)}$, t_i is the failure mileage from smallest to largest for the i-th failure, $x_i = \ln t_i$, $a = -\beta\ln\alpha$, $b = \beta$ $F(t_i)$ adopts median rank estimation method $\hat{F}(t_i) \approx \frac{i-0.3}{n+0.4}$, take $y_i = \ln\ln\frac{1}{1-F(t_i)}$, $x_i = \ln t_i$ into equation(3) and equation(4) can obtain estimation value for a and b. Further, the estimates of α and β is $\hat{\beta} = \hat{b}$, $\hat{\alpha} = \exp(-\hat{a}/\hat{b})$

Based on the discussion above and combining with Table 1 failure data, the final reliability model parameters are:

$\alpha = 1696.5177$, $\beta = 0.8796$

2.1.2. Hypothesis test for reliability model

(1) Linear correlation coefficient test

Linear correlation coefficient is:

$$\hat{\rho} = \frac{\sum_{i=1}^{n} x_i y_i - \frac{1}{n}\sum_{i=1}^{n} x_i \cdot \sum_{i=1}^{n} y_i}{\sqrt{\left[\sum_{i=1}^{n} x_i^2 - \frac{1}{n}(\sum_{i=1}^{n} x_i)^2\right]\left[\sum_{i=1}^{n} y_i^2 - \frac{1}{n}(\sum_{i=1}^{n} y_i)^2\right]}} = \frac{l_{xy}}{\sqrt{l_{xx} \times l_{yy}}} = 1.3782 \tag{9}$$

When $|\hat{\rho}| > \rho_{(n-2,\alpha)}$, there is a significant linear correlation between x and y. Here, $\rho_{(n-2,\alpha)}$ is the critical value of the correlation coefficient ρ which can be looked up in table or calculated by using an approximation formula. In this article, using an approximation formula with a significance level of α =0.1:

$$\rho_{(n-2,\alpha)} = \frac{1.645}{\sqrt{\upsilon+1}} = \frac{1.645}{\mathrm{n}-1} = 0.007 \tag{10}$$

In the equation: $\upsilon = n-2$, n is the cumulative number of failures.

Conducting hypothesis test on the failure distribution of the vehicle system (V) by using correlation coefficient test. From equation (9), $\hat{\rho}$ =1.3782 and $\rho_{(n-2\upsilon)}=0.007$. Thus, since $\hat{\rho} > \rho_{(n-2\upsilon)}$, it is concluded that there is significant relationship between y and x.

(2) d-test hypothesis

Using d test to analyze the failure distance distribution function obtained above. If the distribution function obtained by the parameter estimation follows condition below, the parameter estimation is reasonable and the hypothesis is accepted.

$$D_n = \sup_{-\infty<x<+\infty} \left|F_n(x)-F_0(x)\right| = \max\left\{d_i\right\} \le D_{n,\alpha} \tag{11}$$

In the equation, $F_0(x)$ – assumed distribution function. $F_n(x)$ - empirical distribution function of the sample size of n. $D_{n,\alpha}$ critical value

Specific d_i is derived:

$$d_i = \max\left\{F_0(x_i)-\frac{i-1}{n}, \frac{i}{n}-F_0(x_i)\right\} \tag{12}$$

Performing d-test for the failure distribution function of vehicle system (V): $F(t)=1-\exp[-(\frac{t}{1696.518})^{0.8796}]$ obtained. It is found that D_n =0.0505, while under significance level of 0.1, $D_{n,\alpha}$ = 0.1072. Since $D_n \le D_{n,a}$, the hypothesis is accepted.

2.2. Truck subsystem reliability model

Based on the construction of reliability model regarding vehicle system(V) as a whole, this article divides the failure data of the entire truck into eight subsystems including vehicle frame(VF), Electromagnetic switch(ES), transmission shaft(TS), transmission case(TC), Braking system(BS), mid and rear axles(MR), clutch system(CS), Propelling Rod(PR). Apply independent reliability model analysis to each subsystem. For instance: Table 2 presents the failure process data of the vehicle frame (VF).

Table 2. Vehicle frame (VF) failure mileage data.

i	t_i	i	t_i	i	t_i
1	10	11	430	21	1360
2	10	12	450	22	1860
3	20	13	510	23	2250
4	40	14	590	24	2390
5	70	15	740	25	2410
6	90	16	860	26	2490
7	250	17	1040	27	3180
8	290	18	1040	28	3580
9	380	19	1160	29	5220
10	420	20	1300	30	7780

Based on the method of Perimeter estimation in reliability model from chapter 1.1.1 and failure data(as table 2 shows), the reliability model parameters for the vehicle frame system are:
$\alpha = 1235.6114$, $\beta = 0.6639$

According to the linear correlation coefficient test equations (7) – (8) in section 1.1.2.1, based on table 2, it can be obtained that D_n =0.1088. At significance level of 0.1, $D_{n,\alpha}$ = 0.2976. And according to d test hypothesis equations (9) – (10), based on table 2, $D_{n,\alpha}$ = 0.2976. Since $D_n \le D_{n,a}$, the hypothesis is accepted.

Based on discussion above, the cumulative failure distribution functions and reliability functions of the remaining subsystems can be further obtained. Here, the vehicle system (V) and eight key components' cumulative failure distribution functions and reliability functions are listed in Table 3.

Table 3. Failure distribution function and reliability function of critical components.

I	*System*	*Failure distribution function* $F_i(t)$	*Reliability function* $R_i(t)$	*Failure rate function* $\lambda_i(t)$
1	V	$F_1(t)=1-\exp[-(t/1696.5117)^{0.8796}]$	$R_1(t)=\exp[-(t/1696.5117)^{0.8796}]$	$\lambda_1(t)=\frac{0.8796}{1696.5117}(\frac{t}{1696.5117})^{0.8796}$
2	VF	$F_2(t)=1-\exp[-(t/1235.6114)^{0.6639}]$	$R_2(t)=\exp[-(t/1235.6114)^{0.6639}]$	$\lambda_2(t)=\frac{0.6639}{1235.6114}(\frac{t}{1235.6114})^{0.6639}$
3	ES	$F_3(t)=1-\exp[-(t/1385.0778)^{0.8817}]$	$R_3(t)=\exp[-(t/1385.0778)^{0.8817}]$	$\lambda_3(t)=\frac{0.8817}{1385.0778}(\frac{t}{1385.0778})^{0.8817}$
4	TS	$F_4(t)=1-\exp[-(t/1823.6049)^{0.7857}]$	$R_4(t)=\exp[-(t/1823.6049)^{0.7857}]$	$\lambda_4(t)=\frac{0.7857}{1823.6049}(\frac{t}{1823.6049})^{0.7857}$
5	TC	$F_5(t)=1-\exp[-(t/1694.473)^{0.7724}]$	$R_5(t)=\exp[-(t/1694.473)^{0.7724}]$	$\lambda_5(t)=\frac{0.7724}{1694.473}(\frac{t}{1694.473})^{0.7724}$
6	BS	$F_6(t)=1-\exp[-(t/1837.7141)^{0.7732}]$	$R_6(t)=\exp[-(t/1837.7141)^{0.7732}]$	$\lambda_6(t)=\frac{0.7732}{1837.7141}(\frac{t}{1837.7141})^{0.7732}$
7	MR	$F_7(t)=1-\exp[-(t/1926.9826)^{0.7711}]$	$R_7(t)=\exp[-(t/1926.9826)^{0.7711}]$	$\lambda_7(t)=\frac{0.7711}{1926.9826}(\frac{t}{1926.9826})^{0.7711}$
8	CS	$F_8(t)=1-\exp[-(t/2071.6659)^{1.8645}]$	$R_8(t)=\exp[-(t/2071.6659)^{1.8645}]$	$\lambda_8(t)=\frac{1.8645}{2071.6659}(\frac{t}{2071.6659})^{1.8645}$
9	PR	$F_9(t)=1-\exp[-(t/1744.8638)^{0.8279}]$	$R_9(t)=\exp[-(t/1744.8638)^{0.8279}]$	$\lambda_9(t)=\frac{0.8279}{1744.8638}(\frac{t}{1744.8638})^{0.8279}$

Based on the mathematic model derived, the failure distribution functions F(t) and reliability functions R(t) of each subsystem can be obtained, as shown in Figures 1, 2, 3, and 4.

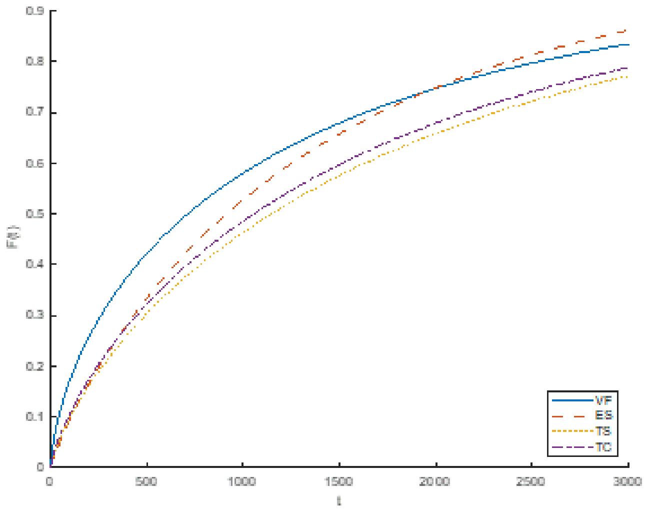

Figure 1. F (t) curve of subsystem.

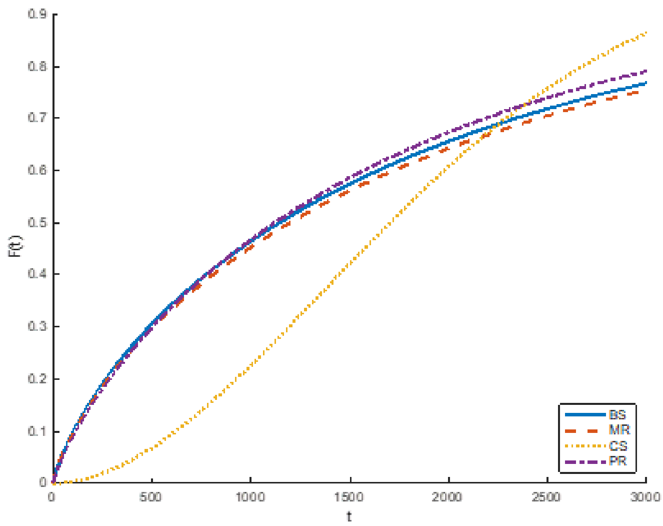

Figure 2. F (t) curve of subsystem.

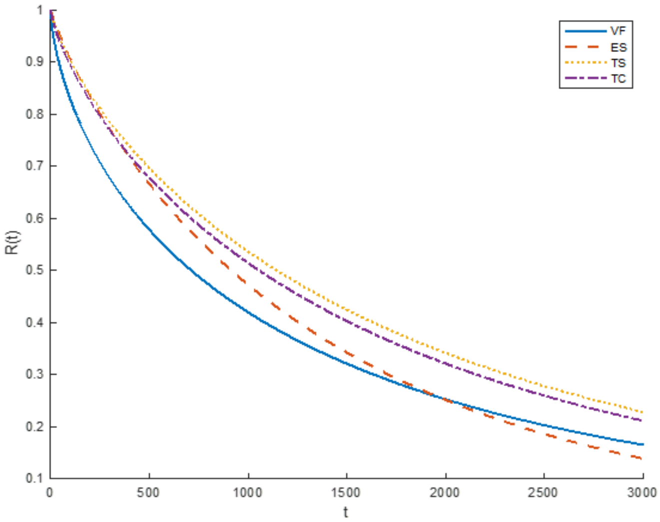

Figure 3. R (t) curve of subsystem.

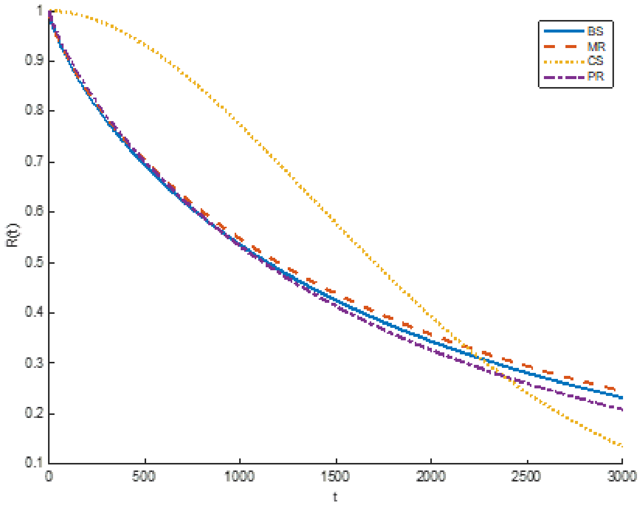

Figure 4. R (t) curve of subsystem.

3. Reliability importance model analysis

3.1. Importance

Probabilistic importance can be conducted to analyze how the subsystem's reliability affects vehicle system (V) reliability. Probabilistic reliability reflects the rate of response of the overall system reliability corresponding to the changes in the reliability of subsystems. The specific formula is:

$$I_i^B = \frac{\partial F_s}{\partial F_i} = \frac{\partial R_s}{\partial R_i} \tag{13}$$

In the equation, I_i^B refers to the importance of the i-th term in terms of the vehicle (V) system probabilistic reliability. F_S, F_i Refers to the vehicle and subsystem failure distribution function correspondingly. R_S, R_i Refers to the vehicle and subsystem reliability function correspondingly.

In vehicle system, each subsystem can operate individually. However, every single subsystem can directly affect the reliability of vehicle system. In other words, the failure of a single subsystem has a significant impact on the reliability of the entire system. Therefore, the reliability for vehicle system (V) can be expressed as the product of the reliability of the individual subsystems, as shown in the following formula:

$$R_s = \prod_{i=1}^{n} R_i \tag{14}$$

This paper would discuss probabilistic importance for 8 subsystems. Using equation (14) can obtain:

$$I_i^B = \frac{\partial R_s}{\partial R_i} = \prod_{\substack{j=1 \\ j \neq i}}^{n} R_j \tag{15}$$

Since this paper include 8 subsystems, n=8. R_1 to R_8 represent vehicle frame (VF), Electromagnetic switch (ES), transmission shaft (TS), transmission case (TC), Braking system (BS), mid and rear axles (MR), clutch system (CS), Propelling Rod (PR).

Take vehicle frame for an example, according to equation (14), $I_1^B = R_2 \cdot R_3 \cdot R_4 \cdot R_5 \cdot R_6 \cdot R_7 \cdot R_8$. Furthermore, according to the reliability function in table 2, $I_1^B = R_2 \cdot R_3 \cdot R_4 \cdot R_5 \cdot R_6 \cdot R_7 \cdot R_8 = \exp[-(t/1235.6114)^{0.6639} - (t/1385.0778)^{0.8817} \ldots\ldots - (t/1744.8638)^{0.8279}]$. The rest probabolistic importance model of subsystems can be also obtained used this method. This paper explores the changes in subsystem importance over distances from 0 to 2000 kilometers, as shown in Figure 5 and Figure 6.

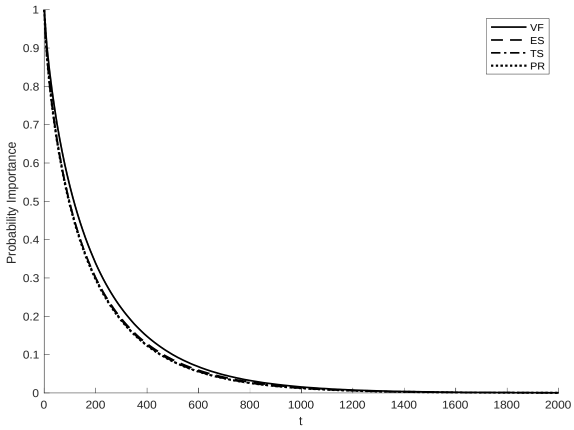

Figure 5. Curves of subsystem probabilistic importance model.

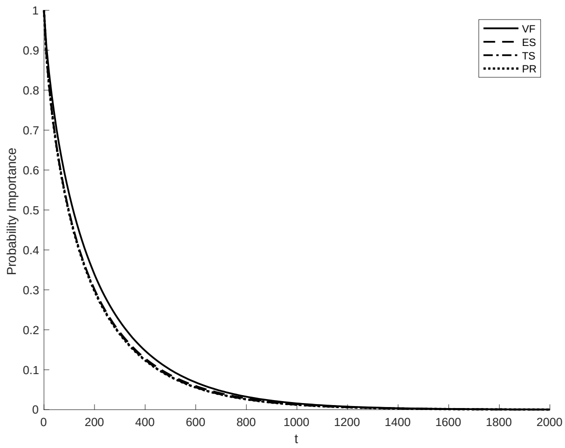

Figure 6. Curves of subsystem probabilistic importance model.

3.2. Importance ranking

In order to be more accurate in representing the importance of key subsystems, the importance ranking of each key subsystem is obtained based on the importance curves. The average method using integration is used to determine the specific importance ranking for each subsystem:

$$\overline{y} = \frac{\int_a^b f(t)dt}{b-a} \tag{16}$$

In this equation, take a=0km, b=2000km. The average importance values of the components are ranked as shown in Table 4. According to the ranking in Table 4, the order of reliability importance for each subsystem is:

Vehicle frame (VF)> Electromagnetic switch (ES)> transmission shaft (TS)> transmission case (TC)> clutch system (CS)> Braking system (BS)> mid and rear axles (MR)> Propelling Rod (PR)

Table 4. Importance ranking for critical subsystem.

		Probabilistic importance	
subsystem	$\overline{I^B}$	subsystem	$\overline{I^B}$
VF	0.6854	CS	0.4800
ES	0.5082	BS	0.4705
TS	0.4812	MR	0.4700
TC	0.4801	PR	0.4700

4. Failure modes and impact analysis

FMECA, Failure Modes and Effect Criticality Analysis, is an effective method for predicting and preventing system failures, as well as a useful tool for analyzing reliability and safety. By summarizing and analyzing known and potential failure modes from historical and collected data, FMECA considers factors such as the frequency of failure occurrence, severity, and urgency under specific conditions to calculate failure criticality. The criticality formula is shown below:

$$C = E \cdot P \cdot T \tag{17}$$

In the equation, E refers to severity; P refers to occurrence frequency; T refers to urgency. The rating scale for these indicators is listed in Table 5 below:

Table 5. Evaluation indicator levels.

levels	occurrence frequency	severity	urgency
1-2	Rarely occurs	Slight	Not urgent
3-5	Occasionally occur	General	Require attention
6-8	Frequently occur	Severe	Urgent resolution
9-10	Very frequently occur	Critical	Require immediate resolution

Table 6. Failure analysis.

Failure description	Subsystem	Frequency P	Severity E	Urgency T	Criticality C
Longitudinal beam cracking	VF	5	9	10	450
Grinding and wear on transmission gears	TC	9	7	9	567
Synchronizer failure	TC	10	6	8	480
Axle steel ring fracture	TC	8	9	8	576
Friction plate and clutch disc damage	CS	9	9	10	810
Cross shaft fracture	TS	5	8	9	360
Flange root fracture	TS	7	6	8	336
flange bolts loosening	TS	7	5	9	315
Main reducer tooth damage	MR	8	7	9	504
Differential case bolt loosening	MR	8	7	9	504
Loose bolts on transmission bearing cap	MR	8	8	9	576

Based on the failure analysis method above, the failure analysis table can be derived, as shown in Table 6. By analyzing the failure modes and criticality of each subsystem, the table reveals that the majority of severe failures occur in the vehicle frame, transmission case, clutch system, and mid and rear axles. For the transmission shaft, failures occur with a relatively low occurrence frequency and severity, but their urgency is still relatively high. Thus, each subsystem's failure would directly and deeply affect the reliability of the vehicle system. Among these failures, the failure criticality of the friction plate and clutch disc damage in the clutch system is the highest, at 810, posing the greatest impact on the vehicle system. By contrast, the failure criticality of loose flange bolts in the transmission shaft system is the lowest (315). While for the clutch system, which has the highest failure criticality, manufacturers should consider improving the load-bearing capacity of the friction plate and clutch disc materials to enhance heat-dissipating capacity. For instance, manufacturers may consider increasing the size of heat dissipation holes in the clutch cover or optimizing the friction plate materials to help improve the performance of the friction plate and disc under excessive load conditions.

5. Conclusion

The article addresses the shortcomings in reliability analysis and modeling between various subsystems in a certain type of truck. By organizing and analyzing the failure data of each subsystem, the reliability modeling of the entire vehicle and its subsystems is established based on the Weibull distribution. After that, hypothesis tests: linear correlation coefficient tests, and D-tests to evaluate the parameter estimation structure.

By establishing the failure distribution functions for the vehicle system and its subsystems, the importance of each subsystem to the overall vehicle system is calculated and analyzed, thus avoiding the need for constructing complex fault trees and making the importance analysis results more accurate and intuitive. The ranking results (as shown in Table 4) indicate that the vehicle frame system has the highest probability of importance, significantly affecting the overall vehicle reliability.

According to the failure mode and impact analysis discussed in the third part of this paper, the fault criticality of the friction plate and clutch disc damage in the clutch system is the highest, with a similarly significant impact on the vehicle system. Based on the analysis above, during the process of improving the reliability of the truck, manufacturers should pay more attention on the vehicle frame and clutch subsystems. For the clutch system, which has the highest fault criticality, manufacturers should consider improving the load-bearing capacity of the friction plate and clutch disc materials to enhance heat dissipation. For instance, increasing the size of heat dissipation holes in the clutch cover or optimizing the friction plate materials can be effective in improving the performance of the friction plate and disc under overload conditions.

The results of this discussion provide essential research methods and references for subsequent discussions and analyses of such types of truck.

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