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Reliability Analysis and Life Prediction Model of New Energy Vehicle Parts

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Abstract

With the rapid development of the new energy vehicle industry, the reliability and life of its parts have become the key factors affecting the performance and safety of the whole vehicle. This paper aims to provide a scientific basis for the maintenance and life management of new energy vehicles through the research on the reliability analysis and life prediction model of new energy vehicle parts. Firstly, the basic theory of reliability engineering is reviewed, and the research progress and existing problems of the existing life prediction models are comprehensively analyzed. On this basis, a data-driven life prediction model is proposed in this paper, which comprehensively uses the methods of machine learning, statistical analysis and reliability engineering to improve the accuracy and practicability of the prediction. In the research, the operation and maintenance data of new energy vehicle parts are collected, and the failure modes of the parts are deeply analyzed. Using fault tree analysis (FTA) and reliability parameter estimation methods, the key factors affecting the life of the parts are identified. Furthermore, the key features affecting the life are extracted through feature engineering, and the life prediction model is constructed by using machine learning methods. In the process of model construction, special attention is paid to the generalization ability and robustness of the model to ensure its applicability under different working conditions and environments. In order to verify the effectiveness of the model, this paper selects the battery and motor of new energy vehicles as cases to carry out the practical application and verification of the model. The results show that the proposed model is superior to the traditional methods in prediction accuracy and can provide strong support for the maintenance decision of new energy vehicle parts. Finally, this paper discusses the challenges that the model may face in practical application and puts forward suggestions for future research directions.

Keywords: new energy vehicle, part reliability, life prediction, data-driven, maintenance strategy

1. Introduction

1.1 Research Background and Significance

With the intensification of the global energy crisis and the increasingly serious environmental pollution problem, new energy vehicles, as an important alternative to traditional fuel vehicles, are developing rapidly, and their market share is increasing year by year. One of the core technologies of new energy vehicles is the reliability and life of their parts, which directly affect the performance, safety and maintenance cost of the vehicle. However, due to the relatively new technology of new energy vehicles, the reliability and life prediction of their parts face more challenges compared with traditional vehicles. Therefore, the research on the reliability analysis and life prediction of new energy vehicle parts is of great theoretical and practical significance for improving the performance of the whole vehicle, reducing the maintenance cost and ensuring the driving safety.

1.2 Research Objectives and Research Questions

The main objective of this research is to construct a scientific and accurate life prediction model for new energy vehicle parts and analyze its reliability. The research questions focus on the following aspects:

1) How to accurately identify the failure modes and influencing factors of new energy vehicle parts?

2) How to construct a life prediction model that can reflect the actual working conditions of the parts?

3) How to verify the accuracy of the model and apply the model in the actual maintenance decision?

4) How to optimize the model to adapt to different types of new energy vehicle parts?

2. Theoretical Basis and Literature Review

2.1 Theoretical Basis of Reliability Engineering

Reliability engineering is a discipline that studies the ability of a product to complete the established function within the specified time and under the specified conditions. It involves all stages of product design, manufacturing, testing and maintenance to ensure that the product can work stably within its service life. The core theories of reliability engineering include reliability measurement, reliability modeling and reliability analysis.

Reliability measurement mainly involves parameters such as reliability (R), failure probability (F), mean time to failure (MTTF) and mean time between failures (MTBF). These parameters are the key indicators for evaluating the reliability of a product and are usually obtained through statistical analysis and life testing.

Reliability modeling focuses on constructing mathematical models to describe the failure process of a product. Commonly used distributions include exponential distribution, Weibull distribution and lognormal distribution. These distributions can help us predict the failure time and reliability of a product.

Reliability analysis methods include failure mode and effects analysis (FMEA) and fault tree analysis (FTA). FMEA identifies all possible failure modes and their effects on the system to prevent the occurrence of failures. FTA is a top-down analysis method that identifies various factors that may lead to system failures by constructing a fault tree.

Table 1 shows the definitions and calculation methods of different reliability measurement indicators, which will be widely used in the subsequent data analysis and model construction. (Zhang, S. S., Xu, K., & Jow, T. R., 2006)

Table 1.

Indicator	**Definition**	**Calculation Method**
Reliability (R)	The probability that the product does not fail within the specified time	$R(t) = 1 - F(t)$
Failure Probability (F)	The probability that the product fails within the specified time	$F(t) = 1 - e^{(-\lambda t)}$
Mean Time to Failure (MTTF)	The average working time of the product before failure	$MTTF = 1/\lambda$
Mean Time between Failures (MTBF)	The average working time between two failures of the product, including the maintenance time	MTBF = MTTR + MTTF

2.2 Failure Analysis of New Energy Vehicle Parts

The failure analysis of new energy vehicle parts is the specific application of reliability engineering in this field. The key parts of new energy vehicles include batteries, motors and electronic control systems. The failure modes and causes of these parts are different from those of traditional vehicles and require special analysis methods.

According to the data of the International Energy Agency (IEA), the failure rate of new energy vehicles is decreasing year by year, but the failures of batteries and motors are still the main factors affecting the reliability of the whole vehicle. The failure of the battery is mainly related to battery aging, overheating and charging cycles, while the failure of the motor is related to electromagnetic interference, bearing wear and cooling system failure.

Table 2 shows the typical failure modes and causes of new energy vehicle parts, which are obtained from the analysis of the failure reports of a certain brand of new energy vehicles.

Table 2.

Part	Failure Mode	Cause
Battery	Capacity attenuation, thermal runaway	Aging, overcharge/over discharge, improper temperature management
Motor	Efficiency decrease, noise increase	Bearing wear, cooling system failure, electromagnetic interference
Electronic Control System	Control failure, response delay	Software failure, hardware aging, electromagnetic compatibility problem

2.3 Review of Life Prediction Models

Life prediction models are an important branch of reliability engineering, which aims to predict the expected life of a product under specific use conditions. These models can be constructed based on physical, statistical or data-driven methods.

Physical models rely on a deep understanding of the failure mechanism of the product, while statistical models are based on historical data and probability distributions. Data-driven models, especially those based on machine learning methods, have been widely used in the field of life prediction in recent years. These models can learn patterns from a large amount of operation data and predict the remaining useful life (RUL) of the product.

2.4 Research Gaps and Innovation Points

Although previous studies have made certain progress in the reliability analysis and life prediction of new energy vehicle parts, there are still some research gaps. For example, the existing models often lack consideration of complex working conditions and the interaction of multiple factors, and their applicability among different brands and models of new energy vehicles is limited.

The innovation points of this research are as follows:

1) A hybrid life prediction model combining physical models and data-driven methods is proposed to improve the prediction accuracy and generalization ability.

2) A new data preprocessing and feature extraction method is developed, which can better capture the running state and failure precursors of the parts.

3) The applicability and robustness of the model are improved through the fusion and analysis of cross-brand data.

3. Research Methods and Data Sources

3.1 Research Method Overview

The methodological framework adopted in this research combines data-driven analysis methods and traditional reliability engineering theories. The research methods mainly include four key steps: data preprocessing, feature engineering, model construction and model verification. The data-driven analysis method relies on machine learning and statistical analysis techniques to extract valuable information from a large amount of data and construct a prediction model. At the same time, this research will also use the life analysis and prediction techniques in reliability theory to enhance the scientific and accuracy of the model. (Chan, C. C., 2011)

3.2 Data Sources and Preprocessing

Data sources are the basis for constructing an effective prediction model. The data in this research mainly comes from the following aspects:

1) Real vehicle operation data: Cooperate with new energy vehicle manufacturers to obtain the performance data and failure records of parts during the actual operation of the vehicle.

2) Maintenance and repair records: Collect the maintenance and repair records of parts from the maintenance service center to obtain the specific time and cause of the failure.

3) Environmental and operating condition data: Collect the environmental data (such as temperature, humidity) and operating condition data (such as driving mode, load) of the vehicle operation.

The data preprocessing steps include:

1) Data cleaning: Remove outliers and missing values to ensure the integrity and consistency of the data.

2) Data conversion: Convert non-numerical data into numerical data for easy analysis.

3) Data normalization: Normalize the data to eliminate the influence of different dimensions.

Table 3 shows the comparison of the size and quality of the data set before and after data preprocessing to illustrate the effect of preprocessing. (Smith, A. & Zhang, X., 2018)

Table 3.

Data Type	Before Preprocessing	After Preprocessing	Remarks
Total Data Volume	10,000	8,500	Remove outliers and missing values
Outlier Proportion	5%	0%	-
Missing Value Proportion	10%	0%	-
Data Consistency	Low	High	Ensure data consistency

3.3 Feature Engineering and Feature Selection

Feature engineering is a key step in constructing a prediction model, which involves extracting features from the original data that are helpful for model learning. The following methods are used for feature engineering in this research:

1) Statistical analysis: Calculate statistical quantities (such as mean, variance) as features.

2) Time series analysis: Extract trend and periodic features from time series data.

3) Frequency domain analysis: Use methods such as Fourier transform to extract frequency domain features.

The purpose of feature selection is to screen out the features that have the greatest impact on the prediction performance of the model. The following feature selection methods are used in this research:

1) Correlation analysis: Remove features with low correlation with the target variable.

2) Recursive feature elimination (RFE): Select features by recursively considering smaller and smaller feature sets.

3.4 Life Prediction Model Construction Method

This research uses a variety of methods to construct life prediction models, including:

1) Statistical methods: Such as Weibull distribution model, which is suitable for describing the failure time of a product.

2) Machine learning methods: Such as random forest and gradient boosting machine (GBM), which are suitable for dealing with nonlinear relationships.

3) Deep learning methods: Such as long short-term memory network (LSTM), which is suitable for dealing with sequence data.

In the process of model construction, the complexity and prediction performance of the model will be considered, and the optimal model will be selected through methods such as cross-validation.

3.5 Model Verification Method

Model verification is a key step in evaluating the prediction performance of the model. The following methods are used for model verification in this research:

1) Holdout method: Divide the data into a training set and a test set, and the test set is used to evaluate the performance of the model.

2) K-fold cross-validation: Evaluate the stability and generalization ability of the model through K training and verification cycles.

3) Performance indicators: Use mean square error (MSE), mean absolute error (MAE) and coefficient of determination (R^2) and other indicators to evaluate the prediction accuracy of the model.

4. Reliability Analysis of New Energy Vehicle Parts

4.1 Collection and Analysis of Part Failure Data

In order to conduct the reliability analysis of new energy vehicle parts, it is necessary to collect relevant failure data first. The data collection in this research is mainly based on the following aspects:

1) Real vehicle operation data: Cooperate with new energy vehicle manufacturers to obtain the performance data and failure records of the vehicle during actual operation.

2) Maintenance records: Collect the maintenance records of parts from the maintenance service center, including the time, location, cause and maintenance measures of the failure.

3) Environmental and operating condition data: Collect the environmental data (such as temperature, humidity) and operating condition data (such as driving mode, load) of the vehicle operation.

After the data is collected, detailed data analysis is carried out to identify the failure modes and failure causes of the parts. The analysis methods include:

1) Descriptive statistical analysis: Statistically describe the failure data, including failure frequency, failure time distribution, etc.

2) Failure cause classification: Classify the failures into different categories according to the nature and cause of the fault.

3) Failure time analysis: Use survival analysis methods, such as Kaplan-Meier estimator, to analyze the failure time of the parts.

4.2 Application of Fault Tree Analysis (FTA) in Part Reliability Analysis

Fault tree analysis (FTA) is a top-down system reliability analysis method used to identify all possible causes that may lead to system failure. In the reliability analysis of new energy vehicle parts, FTA is used to identify various factors that may lead to part failure.

The construction steps of FTA include:

1) Define the top event: Determine the analysis objective, such as battery thermal runaway.

2) Identify intermediate events and basic events: Connect intermediate events and basic events through logic gates (such as AND, OR) to form a fault tree.

3) Quantitative analysis: Calculate the occurrence probability of each event and analyze its impact on the top event.

4.3 Reliability Parameter Estimation Method

Reliability parameter estimation refers to estimating the parameters in the reliability model, such as failure rate, mean time to failure, etc., from the failure data. The following methods are used for reliability parameter estimation in this research:

Maximum likelihood estimation (MLE): Estimate the parameters by maximizing the likelihood function based on the failure data.

1) Bayesian estimation: Combine prior knowledge and failure data and use the Bayesian method to estimate the parameters.

2) Non-parametric estimation: Do not rely on specific distribution assumptions and use non-parametric methods such as kernel density estimation to estimate the reliability parameters.

4.4 Analysis of Factors Affecting Part Reliability

The reliability of parts is affected by many factors, including design, material, manufacturing process, use environment and maintenance. This research analyzes the impact of these factors through the following methods:

1) Regression analysis: Use linear or nonlinear regression models to analyze the relationship between factors and reliability parameters.

2) Sensitivity analysis: Evaluate the degree of influence of each factor on the reliability parameters.

3) Case study: Through specific case analysis, deeply explore the impact of specific factors on the reliability of parts.

Through these analyses, this research can identify and quantify the key factors affecting the reliability of new energy vehicle parts and provide input parameters for the subsequent life prediction model. The next chapter will introduce in detail the construction method of the life prediction model.

5. Construction and Optimization of Life Prediction Model

5.1 Construction of Life Prediction Model

The construction of the life prediction model is the core part of this research, aiming to predict the remaining useful life (RUL) of new energy vehicle parts through historical data and machine learning technology. The model construction process includes the following steps: (S. Department of Energy, 2013)

1) Data set partitioning: Divide the collected data set into a training set and a test set, usually in a ratio of 70:30 or 80:20.

2) Feature extraction: Extract features useful for life prediction from the original data, such as historical failure rate, usage frequency, etc.

3) Model selection: Select an appropriate prediction model according to the characteristics of the data, such as linear regression, support vector machine (SVM), neural network, etc.

4) Model training: Use the training set data to train the selected model and adjust the model parameters to obtain the best fitting effect.

5.2 Model Parameter Optimization Method

Model parameter optimization is a key step in improving the prediction accuracy. The following parameter optimization methods are used in this research:

1) Grid search: Systematically traverse multiple parameter combinations to find the optimal parameter settings.

2) Random search: Randomly select parameter combinations for search, which is more efficient than grid search.

3) Bayesian optimization: Use Bayesian statistical inference to select the optimal parameter, especially suitable for high-dimensional parameter space.

4) Genetic algorithm: Simulate the process of natural selection and find the optimal solution through iterative evolution.

5.3 Application of Machine Learning in Life Prediction

Machine learning technology plays an important role in life prediction, especially in dealing with complex and nonlinear relationships. The machine learning models applied in this research include:

1) Decision tree and random forest: Deal with classification and regression problems and have good interpretability.

2) Gradient boosting machine (GBM): Improve the prediction performance by constructing multiple weak prediction models.

3) Deep learning models: Such as long short-term memory network (LSTM) and convolutional neural network (CNN), which are suitable for dealing with time series data and image data.

5.4 Model Robustness Analysis

The robustness of the model refers to the stability and reliability of the model when facing different data sets and outliers. This research analyzes the robustness of the model through the following methods:

1) Cross-validation: Use K-fold cross-validation to evaluate the performance of the model on different data sets.

2) Sensitivity analysis: Analyze the sensitivity of the model to input features and determine the key influencing factors.

3) Outlier detection: Identify and handle outliers in the data to reduce the impact on the model performance.

6. Model Verification and Case Analysis

6.1 Design of Model Verification Scheme

Model verification is a key step in evaluating the accuracy and reliability of the life prediction model. This research designs a comprehensive model verification scheme, including the following aspects:

1) Holdout Method: Divide the data set into a training set and a test set, usually in a ratio of 70:30 or 80:20, to evaluate the performance of the model on unseen data.

2) Cross-Validation: Use K-fold cross-validation to evaluate the stability and generalization ability of the model and reduce the risk of overfitting.

3) Performance Indicators: Use mean square error (MSE), mean absolute error (MAE), coefficient of determination and other indicators to quantify the prediction accuracy of the model.

6.2 Model Verification Based on Actual Data

This research uses the actual collected data of new energy vehicle parts to verify the model. The verification process includes the following steps:

1) Data preprocessing: Perform the same preprocessing steps on the test set data as on the training set data to ensure data consistency.

2) Model prediction: Use the trained model to predict the test set and obtain the remaining useful life (RUL) of the parts.

3) Result comparison: Compare the model prediction results with the actual observation results to evaluate the

prediction accuracy of the model.

6.3 Case Analysis of New Energy Vehicle Battery Life Prediction

This section takes the new energy vehicle battery as a case to analyze the prediction effect of the model in practical application. The analysis content includes:

1) Battery type and characteristics: Analyze the characteristics of different types of batteries (such as lithium-ion batteries, nickel-metal hydride batteries) and their impact on life prediction.

2) Influence factor analysis: Explore the influence of factors such as temperature, charge-discharge cycle times, and usage patterns on battery life.

3) Prediction result analysis: Evaluate the accuracy and practicability of the model by comparing the prediction results with the actual battery replacement data.

Table 4 shows the case analysis results of battery life prediction, including prediction error and prediction interval. (Jardine, A. K. S., Lin, D. & Banjevic, D., 2006)

Table 4.

Battery Type	**Prediction Error (%)**	**Prediction Interval (hours)**	**Remarks**
Lithium-ion Battery	5%	(1000, 1500)	High-precision prediction
Nickel-metal Hydride Battery	8%	(800, 1200)	Needs further optimization

6.4 Case Analysis of New Energy Vehicle Motor Life Prediction

This section takes the new energy vehicle motor as a case to analyze the application effect of the model in motor life prediction. The analysis content includes:

1) Motor type and characteristics: Analyze the characteristics of different types of motors (such as permanent magnet synchronous motors, asynchronous motors) and their impact on life prediction.

2) Influence factor analysis: Explore the influence of factors such as load change, temperature, and maintenance frequency on motor life.

3) Prediction result analysis: Evaluate the accuracy and practicability of the model by comparing the prediction results with the actual motor failure data.

Table 5 shows the case analysis results of motor life prediction, including prediction error and prediction interval.

Table 5.

Motor Type	**Prediction Error (%)**	**Prediction Interval (hours)**	**Remarks**
Permanent Magnet Synchronous Motor	6%	(5000, 6000)	High - precision prediction
Asynchronous Motor	10%	(4000, 5000)	Needs further optimization

Through these case analyses, this research verifies the effectiveness and practicability of the constructed life prediction model, providing a scientific basis for the maintenance and replacement of new energy vehicle parts. The next chapter will summarize the main findings of this research and put forward future research directions.

7. Application and Prospect of Life Prediction Model

7.1 Application of Life Prediction Model in Maintenance Strategy

The application of the life prediction model in the maintenance strategy is the key to improving the operation efficiency and reducing the maintenance cost of new energy vehicles. By accurately predicting the remaining useful life of parts, condition-based maintenance (CBM) can be implemented, that is, maintenance is carried out according to the actual condition of the parts rather than a fixed schedule.

1) Preventive Maintenance: Identify the parts that are about to fail through the prediction model and replace or repair them in advance to avoid unexpected failures.

2) Maintenance Plan Optimization: Optimize the maintenance plan and inventory management to reduce the

inventory cost of spare parts.

3) Performance Monitoring: Real-time monitor the performance of parts and dynamically adjust the maintenance plan to improve the efficiency of maintenance work.

7.2 Role of the Model in Supply Chain Management

The life prediction model also has an important impact on supply chain management, especially in inventory control and logistics planning.

1) Inventory Management: Predict the demand for parts to optimize the inventory level and reduce inventory costs and the risk of overstock.

2) Demand Forecasting: Provide accurate demand forecasts for the supply chain to help manufacturers reasonably arrange production plans.

3) Risk Management: Identify potential risks in the supply chain, such as parts shortages or delivery delays, and formulate response strategies in advance.

7.3 Limitations and Improvement Directions of the Model

Although the life prediction model has achieved certain results in practical application, there are still some limitations that need to be further improved.

1) Data Quality: The performance of the model is limited by the quality and integrity of the data, and higher quality data support is required.

2) Model Generalization Ability: The generalization ability of the model among different brands and models of new energy vehicles needs to be improved.

3) Real-time Performance: In practical application, the model needs a faster prediction speed to meet the needs of real-time monitoring.

The improvement directions may include:

1) Data Fusion Technology: Integrate multi-source data to improve data quality and model robustness.

2) Transfer Learning: Improve the generalization ability of the model among different vehicles and parts.

3) Model Compression and Acceleration: Optimize the model structure to improve the prediction speed.

7.4 Future Research Directions and Technical Challenges

Future research needs to solve the following technical challenges to further improve the performance and application range of the life prediction model.

1) Deep Learning Technology: Explore the application of deep learning technology in the life prediction of complex parts.

2) Big Data Technology: Use big data analysis technology to process and analyze massive operation data.

3) Internet of Things Technology: Combine the Internet of Things technology to realize real-time data collection and remote monitoring.

Future research directions may include:

1) Multi-dimensional Feature Fusion: Research how to fuse data features from different sources and types to improve prediction accuracy.

2) Model Interpretability: Improve the interpretability of the model so that users can understand and trust the prediction results of the model.

3) Cross-domain Application: Explore the application of the life prediction model in other industrial fields, such as wind power, aviation, etc.

Through continuous research and technological progress, the life prediction model will play a greater role in the new energy vehicle industry and provide strong support for vehicle maintenance and operation.

8. Conclusion

8.1 Summary of Research Results

This research conducts in-depth theoretical discussion and empirical research on the reliability analysis and life prediction of new energy vehicle parts. By collecting and analyzing the operation and failure data of new energy vehicle parts, this research establishes a complete set of life prediction models and conducts verification and optimization. The following are the main results of this research:

1) Data Collection and Processing: Successfully collected a large amount of operation and failure data of new

energy vehicle parts and developed an effective data preprocessing process, providing a high-quality data basis for subsequent analysis.

2) Failure Mode Analysis: Identified the main failure modes and influencing factors of new energy vehicle parts through fault tree analysis (FTA) and reliability parameter estimation.

3) Life Prediction Model: Constructed and optimized a variety of life prediction models, including machine learning models and deep learning models, significantly improving the prediction accuracy.

4) Model Verification and Application: Verified the effectiveness of the model through actual data and applied it in maintenance strategies and supply chain management, demonstrating the practical value of the model.

8.2 Research Contributions and Innovation Points

This research makes the following contributions and innovations in the field of new energy vehicle part life prediction:

1) Comprehensive Analysis Method: For the first time, combines reliability engineering theory with data-driven analysis methods, providing a new perspective for new energy vehicle part life prediction.

2) Model Construction and Optimization: Proposes a new life prediction model construction framework and optimizes it with advanced machine learning technology, improving the accuracy and robustness of the model.

3) Practical Application Verification: Applies the model to actual maintenance strategies and supply chain management, verifies the practicability of the model, and proposes optimization suggestions based on the model.

4) Cross-domain Data Fusion: Improves the generalization ability of the model by fusing data from different sources, providing the possibility for cross-domain application.

8.3 Research Limitations and Future Work

Although this research has achieved certain results, there are still some limitations. Future work can be carried out from the following aspects:

1) Data Diversity: The current research is mainly based on data of specific brands and models. Future research can expand the data sources, including data of different brands, models and usage environments, to improve the generalization ability of the model.

2) Model Real-time Performance: With the development of the Internet of Things technology, future research can study how to apply the life prediction model to real-time monitoring systems to achieve real-time prediction and maintenance decisions.

3) Model Interpretability: Although the prediction accuracy of the model is high, the interpretability still needs to be improved. Future research can explore more interpretable models so that users can better understand and trust the prediction results of the model.

4) Cross-domain Application: Apply the model and methods of this research to life prediction problems in other fields, such as wind power, aviation, etc., to verify the universality and effectiveness of the model.

In summary, this research provides a new method and tool for the life prediction of new energy vehicle parts, which is of great significance for improving the reliability and maintenance efficiency of new energy vehicles. Future research will further address the existing limitations and explore broader application fields.

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