information

MDPI

Article

Research on the Construction of an Evaluation Index System for Onboard Equipment Status Based on Real-Time Data Analysis

Fumin Zou [1,2], Ting Ye [1,2,*] and Feng Guo [1,2]

[1] Fujian Key Laboratory of Automotive Electronics and Electric Drive, Fujian University of Technology, Fuzhou 350118, China; fmzou@fjut.edu.cn (F.Z.); mapli@fjut.edu.cn (F.G.)
[2] Renewable Energy Technology Research Institute, Fujian University of Technology, Fuzhou 350118, China
* Correspondence: 2221905021@smail.fjut.edu.cn; Tel.: +86-188-5076-7655

Abstract: The research explores methods for onboard real-time data analysis and health status assessment, focusing on the working principles and status assessment theory of onboard equipment in the electronic toll collection (ETC) system. By applying AHP, fuzzy comprehensive evaluation method, entropy method, and Delphi method, a practical health status assessment model for onboard equipment has been established, providing an innovative path for dynamic real-time monitoring of onboard devices. The research first constructs an indicator system and assessment model, combining expert scoring with fuzzy judgment to objectively quantify the status of onboard equipment, ultimately resulting in a health status assessment indicator system for the objects under evaluation. During the assessment process, expert scoring is used to determine the subjective weights via AHP, and the combined weights are derived by incorporating objective weights, with instance results showing that the comprehensive weights of various indicators lie between the subjective and objective weights. The research also utilizes the Weibull distribution to simulate the failure rate of onboard equipment, indicating that the failure modes of the onboard devices are closely related to their operational status, providing a theoretical basis for future technological improvements. Through empirical analysis of the assessment model, the research verifies the superiority of the comprehensive weights and emphasizes its new approach in health status assessment of onboard devices, opening up new avenues for research in related fields.

Keywords: health status evaluation of onboard equipment; real-time data analysis; analytic hierarchy process; fuzzy comprehensive evaluation; entropy method; Delphi method

check for updates

Academic Editor: Aneta Poniszewska-Maranda

Received: 9 October 2024
Revised: 29 October 2024
Accepted: 30 October 2024
Published: 31 December 2024

Citation: Zou, F.; Ye, T.; Guo, F. Research on the Construction of an Evaluation Index System for Onboard Equipment Status Based on Real-Time Data Analysis. *Information* **2025**, *16*, 15. https://doi.org/10.3390/info16010015

1. Introduction

With the rapid development of modern transportation systems, the application of onboard equipment in vehicle management, toll collection, and monitoring is becoming increasingly widespread. Particularly in the electronic toll collection (ETC) system [1], the health status of onboard equipment directly impacts the reliability and efficiency of the system. Therefore, conducting real-time data analysis and health status evaluation of onboard equipment is of utmost importance [2–4]. This need has spurred research into the establishment of an evaluation index system for the health status of onboard equipment, aiming to achieve comprehensive monitoring and assessment of equipment health through scientific methodology [5,6].

As a key component of intelligent transportation systems, the ETC system relies on Internet of Things technology to achieve autonomous recognition and toll collection of vehicles through the rapid collection and processing of vehicle information. This process is primarily accomplished through microwave communication between the onboard unit and the roadside unit, enabling the system to automatically detect and charge when a vehicle passes through the toll gantry. Existing ETC systems are complex, typically consisting of onboard units, controller units, detection units, and onboard management software to ensure efficient collaboration within the system. The good coordination among these devices not only improves toll collection efficiency but also significantly enhances the intelligence of traffic management.

In recent years, with the continuous advancement of technology, the diversity and complexity of onboard equipment have been increasing [7]. This presents significant challenges to traditional equipment status evaluation methods, making it difficult to effectively implement comprehensive monitoring of equipment status [8,9]. To address this issue, researchers have begun to combine multi-source data fusion technology to explore how to utilize real-time data and advanced evaluation models to enhance the status monitoring capabilities of onboard equipment. This research aims not only to overcome the limitations of traditional methods but also to provide new perspectives for future technology development and research, driving further innovation and advancement in the industry.

The core objective of this research is to establish an evaluation index system for the health status of onboard equipment based on real-time data analysis. Using the analysis of existing onboard equipment data and status variables, an evaluation system for onboard equipment has been developed from the aspects of evaluation accuracy, reliability, component configuration, operating environment, and safety. Specifically, the research will utilize the analytic hierarchy process (AHP) to determine the subjective weights of the evaluation system and the entropy method to determine the objective weights of the evaluation indicators, thereby improving the accuracy of each indicator within the evaluation system [10]. This process requires the integration of technical specifications for vehicle configuration to form a three-layer index system dominated by goal, criterion, and factor layers.

In the specifics of indicator construction, the accuracy indicator focuses on evaluation errors of the onboard equipment, the status of functional modules, operational errors, and communication errors. The evaluation error is calculated based on the relationship between measured values and evaluated values, with different accuracy level requirements established in the standards for various evaluation errors. Additionally, the reliability indicator considers family defects and operational time indices; it is essential to take into account family defect records from the manufacturers of the onboard equipment to avoid erroneous impacts on the status assessment [11].

The assessment of component configuration mainly includes enclosure integrity, communication errors, and component qualification rates, with enclosure integrity referring to the completeness and damage of critical devices like wiring boxes and signal input/output components. Furthermore, the evaluation of the operating environment of the equipment is also crucial, involving factors such as temperature, humidity, and electromagnetic compatibility, which directly affect the performance and lifespan of internal electronic components within the onboard equipment.

Lastly, safety requirements are an indispensable part of constructing the index system, which mainly includes communication safety, electrical safety, and operational parameters; all must meet the specific technical standards and national requirements for equipment operation.

Overall, this research aims to provide solid theoretical support and practical guidance for enhancing the operational safety and service quality of onboard equipment through comprehensive analysis and in-depth exploration of real-time data. Furthermore, the research will explore the application of emerging technologies in this field, such as artificial intelligence and big data analysis, to promote the efficient, stable, and safe operation of the entire intelligent transportation system. Through the integration of these research findings, the research hopes to provide more forward-looking and practical guidance for the maintenance of onboard equipment, contributing to the development of intelligent transportation.

2. Relevant Methodological Analyses

2.1. Hierarchical Analysis

Hierarchical analysis has a wide range of applications in condition assessment, and quantitative analysis of qualitative factors requires the establishment of a hierarchical assessment structure and the analysis of the relationship between indicators at each level. The determination of subjective weights using the hierarchical analysis method is based on the scores of experts, and the indicators are divided to obtain a certain level of correlation, using the comparison of the relative importance of the two elements to establish a discriminant matrix, and the main comparison is based on the scores of experts [12].

2.2. Fuzzy Comprehensive Judgment Method

The fuzzy comprehensive judgment method is to use the affiliation function to transform the qualitative assessment into quantitative assessment, which can be divided into multi-layer multi-assessment, single-layer multi-assessment, and single-layer single-item assessment, and use different assessment methods according to the assessment of the target, in which the core of the fuzzy comprehensive judgment method for state assessment is to determine the affiliation function [13]. Compared with the hierarchical analysis method, the fuzzy nature of the judgment proof can be used, reducing the reliance on judging the importance of the target.

The steps to implement the fuzzy composite judgment method are as follows:

1. Establishment of a factor set of objectives to be assessed.

The first step is to create a set of indicators for the object to be assessed. If the object to be assessed has m sub-indicators at the bottom level, that is as follows [14]:

$$U = \{u_1, u_2, \cdots, u_m\} \tag{1}$$

The upper level of the object to be assessed has k indicators, which can be represented as a subset based on the affiliation between the objects to be assessed as follows:

$$U = \{u_1, u_2, \cdots, u_k\} \tag{2}$$

2. Establishment of a hierarchy of assessment criteria.

If an indicator of the assessed object corresponds to l evaluation criteria, the state of the in-vehicle equipment is classified as very good, fair, poor, and very poor, according to the set of rubrics for vehicle safety [15].

3. Calculation of the weights of the lowest and upper indicators of the object to be assessed, respectively.

The weight vector of the underlying indicators of the assessment object to be measured is calculated using the following formula:

$$W = \{w_1, w_2, \cdots, w_l\}^T_{k\times m} \tag{3}$$

4. Determine the appropriate affiliation function according to the object to be assessed and calculate the affiliation value of the rubric set for each indicator so as to obtain the affiliation matrix of the assessment indicators of the object to be assessed, in which the affiliation matrix composed of all the assessment indicators at the bottom is noted as R.

5. Calculate for the evaluation vector B.

The computational formula for the evaluation vector B is as follows:

$$B = W \cdot R = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_k \end{bmatrix}_{k \times m} \cdot \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1l} \\ r_{21} & r_{22} & \cdots & r_{2l} \\ \vdots & \vdots & \vdots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{ml} \end{bmatrix}_{m \times l} = \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1l} \\ b_{21} & b_{22} & \cdots & b_{2l} \\ \vdots & \vdots & \vdots & \vdots \\ b_{k1} & b_{k2} & \cdots & b_{kl} \end{bmatrix}_{k \times l} \quad (4)$$

6. Calculate the evaluation vector of the target to be evaluated μ.

If the weights of the upper level indicators of the assessment object are obtained, then the we calculate the following:

$$w = \{w_1, w_2, \cdots, w_k\}_{l \times k} \quad (5)$$

The obtained evaluation vector μ is computed as follows:

$$\begin{aligned} \mu = w \cdot B = [w_1, w_2, \cdots, w_k]_{k \times m} \cdot \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1l} \\ b_{21} & b_{22} & \cdots & b_{2l} \\ \vdots & \vdots & \vdots & \vdots \\ b_{k1} & b_{k2} & \cdots & b_{kl} \end{bmatrix}_{k \times l} \\ = [\mu_1, \mu_2, \cdots, \mu_l]_{1 \times l} \end{aligned} \quad (6)$$

7. According to the steps in the above numbers the vectors and states of the evaluated objects can be obtained.

2.3. Entropy Method

The entropy weight method is a comprehensive ancient evaluation method that uses the information entropy of each indicator to determine the degree of importance in the evaluation indicators based on the information obtained from each factor, based on the establishment of the indicator evaluation system, taking into account all the factors in a comprehensive manner, so that each indicator can be passed on to the evaluator, and the weights are determined according to the size of the information corresponding to each indicator [16].

1. Determination of the criteria matrix Y.

After determining the standardized matrix for the sample data of the data specification indicator, that is:

$$Y = (y_{ij})_{m \times n} \quad (7)$$

2. Calculation of the entropy value of the indicator.

If e_i is used to represent the entropy value of the assessment indicator i can be obtained:

$$\begin{cases} e_i = -\dfrac{1}{\ln(m)} \sum\limits_{j=1}^{n} f_{ij} \ln(f_{ij}) \\ f_{ij} = \dfrac{y_{ij}}{\sum\limits_{j=1}^{n} y_{ij}} \end{cases} \quad (8)$$

In Equation (8), m represents the number of datasets in the data sample.

3. Calculate the redundancy of entropy.

The entropy redundancy used is calculated as follows:

$$d_i = 1 - e_i \tag{9}$$

4. Calculation of entropy weights for assessment indicators.

For the evaluation of the indicators of the fiducial entropy weights are calculated as follows:

$$w_i = \frac{d_i}{\sum\limits_{j=1}^{n} d_j} \tag{10}$$

5. Calculation of the consolidated assessment value S_i.

Calculations are performed based on the calculated composite assessment value S_i and are ranked according to the obtained calculations, using the following formula:

$$S_i = \sum_{j=1}^{n} w_i y_{ij} \tag{11}$$

2.4. The Delphi Method

The Delphi method is a common method in the assignment of indicator weights, which can quickly and conveniently obtain the weights of assessment indicators, and it is to use experts in the field of assessment to score the indicators, making full use of the experience and knowledge of the experts, so this method is also called the expert scoring method [17]. The expert scoring method is commonly used to determine the subjective weights of indicators, but this method needs to rely on the experience and opinions of experts and is easily affected by the subjectivity of experts, so it is generally used in conjunction with some objective and quantitative methods to ensure that the weights of indicators are determined accurately.

The specific process of applying the Delphi method is as follows:

1. Concentration of opinions E.

The calculation of the exclusive price recognition is used to obtain the opinion concentration E:

$$E = \frac{1}{m} \sum_{i=1}^{m} a_i \tag{12}$$

2. Calculation of the degree of expert disagreement.

After calculating the degree of expert disagreement, the degree of opinion dispersion δ was obtained as follows:

$$\delta = \sqrt{\frac{1}{m-1} \sum_{i=1}^{m} (a_i - E)^2} \tag{13}$$

In Equation (13), E represents the level of recognition.

3. Determination of the end of the judgment call.

The judgment of whether the consultation is closed or not is based on the expert approval rating and the calculated expert disagreement rating, using the lower limit value of the expert approval rating E_0 and the expert disagreement rating δ_0, i.e., yes, written as follows:

$$E_i > E_0, \delta_i > \delta_0 \tag{14}$$

2.5. Condition Assessment Process

The main health index indicators used in health condition assessment correspond to the different states of the assessed objects, and with the application of the health index theory in the condition assessment of equipment in various fields, a certain connection has been established between the health index and the state of the equipment as well as the failure rate, as shown in Table 1.

Table 1. Relationship between health indices and equipment condition and failure rates.

Health Index Ranges	Device Status	Failure Rate
0~3	an excellent	very low
3~5.5	usual	lower (one's head)
5.5~7	differ from	middle
7~10	poorly	your (honorific)

According to the application of health index theory in the field of equipment state evaluation, it is necessary to establish a health state evaluation system, take the factors affecting the health state into account in the construction of the index system, and establish a multifactorial target decision-making, including the evaluation indexes, the weights of the indexes, and the state evaluation model, in order to be able to evaluate the health state of the vehicle-mounted equipment and realize the prediction of the operating state of the vehicle-mounted equipment, with multiple In order to be able to assess the health state of the onboard equipment and achieve the prediction of the operating state of the onboard equipment [18,19], the evaluation indexes are taken as the research basis, and the method of quantitative calculation of the weights of the indexes is used to evaluate the state of the onboard equipment corresponding to a certain moment or a certain period of time [20], which can be divided into three steps:

1. Obtain a system of key indicators related to the health state of onboard equipment and the amount of onboard equipment state corresponding to each indicator;
2. Classify the importance and evaluation role of each indicator in the evaluation system of the health state, that is, to calculate the weight of the indicators in the indicator system and obtain the weight value of different indicators for the assessment of the health state of the vehicle-mounted equipment;
3. Substituting the obtained weight values of different indicators into the evaluation model, the current state of health is assessed according to the obtained amount of onboard equipment operating status.

Combined with the actual operation and operation and maintenance data of onboard equipment and the structural characteristics of the ETC system, the health state assessment process of onboard equipment is established as shown in Figure 1.

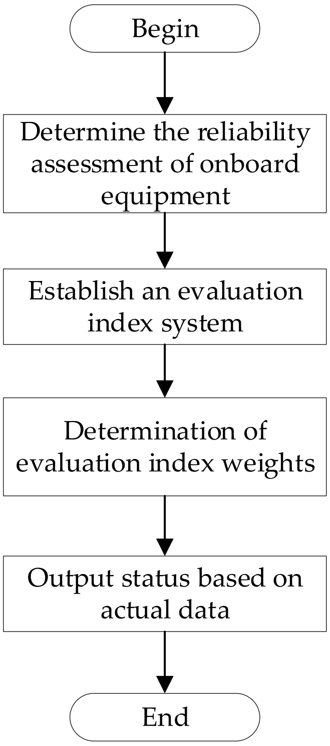

Figure 1. Flowchart of onboard equipment health state assessment.

3. Real-Time Data Analysis and Processing Model

3.1. Data Presentation and Related Notes

The experimental dataset used in this research is derived from the transaction records of a motorway ETC system in a Chinese province from 1 to 5 June 2021, which contains both ETC transaction data and CPC transaction data. A total of about 31 million transaction data were collected, involving about 1.33 million vehicles, which include four types of passenger cars, six types of trucks, and six types of special operation vehicles. The gantry data, shown in Table 2, contain the desensitized vehicle identification, transaction time, transaction error code, and trip number, as well as the number, name, type, and location information of the gantry. The entrance toll booth data are shown in Table 3 and contain information such as the desensitized vehicle identification, the number, name, type, and location of the entrance toll booth, as well as the vehicle transaction time, trip number, and error code. Similarly, the exit toll booth data are shown in Table 4 and contains desensitized vehicle identification, exit toll booth number, name, type, location, and vehicle transaction time, trip number, and error code information.

Table 2. Description of selected fields in the gantry transaction data.

Field Name	Field Properties	Typical Example
GantryID	Gantry number	349E61
GantryName	Name of the gantry	Jinghai to Nanzhou
GantryType	Gantry type	2
TradeTime	Gantry trading hours	1 June 2021 08:00:00
OBUid	Vehicle identification	1775853281
PassID	Itinerary No.	0123. 741
GantryPos	Gantry position	(119.308, 25.888)
ErrorCode	Transaction error code	1

Table 3. Description of some of the fields in the entry toll booth transaction data.

Field Name	Field Properties	Typical Example
EnstationID	Entrance toll station number	2100
EnstationName	Name of entrance toll station	Jinghai Toll Station
StationType	Type of toll station	0
EnTime	Entrance trading hours	1 June 2021 08:00:00
OBUid	Vehicle identification	1775853281
PassID	Itinerary No.	0123. 741
EnstationPos	Entrance toll station location	(119.308, 25.888)
ErrorCode	Transaction error code	1

Table 4. Description of some fields in the exit toll booth transaction data.

Field Name	Field Properties	Typical Example
ExstationID	Exit toll station number	2100
ExstationName	Name of exit toll booth	Jinghai Toll Station
StationType	Type of toll station	1
ExTime	Export trading hours	1 June 2021 08:00:00
OBUid	Vehicle identification	1775853281
PassID	Itinerary No.	0123. 741
ExstationPos	Location of exit toll booths	(119.308, 25.888)
ErrorCode	Transaction error code	1

This table shows the description of some of the ETC data fields. passID is used as a unique identifier to pinpoint each trip, the ErrorCode field is used to record the status of each transaction, where 0 means the transaction is normal and 1 means the transaction is abnormal, and the OBUid is the OBU device number used to uniquely identify the vehicle.

In the process of analyzing the ETC and CPC transaction data, we found that there are many fields with similar attributes in the data, such as number, name, and type. These similarities help us to better understand and mine the correlation between these data for fusion between transaction data.

3.2. Real-Time Data Feature Extraction

The real-time data from onboard equipment varies significantly over time. Even for the same onboard equipment under the same conditions, some indicator data will change with time. Real-time data can be categorized into cross-sectional data and time series state data:

1. Cross-Sectional Data: Cross-sectional data, also known as static data, refer to the test data results from different test subjects at the same time point or within the same time period, reflecting the intrinsic numerical relationships between different phenomena at the same time [21]. When analyzing cross-sectional data (i.e., selecting the test data for a specific time), it is necessary to ensure the reliability and completeness of the selected data. For example, the data should be obtained from tests conducted at regularly spaced intervals and should cover the full frequency range of the equipment. This way, the patterns derived from the data will maximally describe the variation of a certain parameter of a particular type of equipment.
2. Time Series State Data: Time series state data refer to the state data of a phenomenon for the same test subject under identical conditions at different time points, reflecting how the phenomenon changes over time. The selection of time series data requires that the testing process has good repeatability, ensuring that for the same equipment and the same parameters, the testing conditions and environments remain as consistent as possible across different time points. For instance, variations in the settings of testing equipment, instrument connections, and electromagnetic environments can impact

parameter changes, leading to parameters that do not accurately reflect temporal variations [22]. Therefore, when selecting data, it is required that the tested vehicles, devices, testing instruments, and cables, as well as testing layouts, remain as consistent as possible.

3. Combination of Qualitative and Quantitative Indicators: The evaluation indicators established include both qualitative and quantitative types. Quantitative indicators consist of values presented in a quantitative form derived from the objective data acquired. Based on these quantitative values, the operational status of the onboard equipment can be evaluated. Qualitative indicators rely on the experience and knowledge accumulated by experts or staff to assign scores, which are used to assess the operating status of the onboard equipment. In constructing the evaluation index system, it's vital to consider the objectivity of the indicators while also reflecting their empirical nature, thus achieving a balanced ratio of quantitative and qualitative indicators [23].
4. Data Hierarchy: In the construction of the indicator system, it is also necessary to consider the hierarchy among the indicators. This not only simplifies the assessment process but also demonstrates the interrelationships between the indicators. Therefore, when establishing the indicator system, each indicator must first be classified and categorized to clarify and simplify the relationships between them.

3.3. Data Processing Model

Based on the analysis of existing operational data and state variables of onboard equipment, it is known that there are occurrences of data loss and anomalies. To address stability issues caused by environmental influences during the vehicle's operational process, there may be data drops or storage failures in the onboard equipment when storing or receiving data, leading to missing data packets.

Thus, before using onboard equipment for state evaluation, it is necessary to analyze the completeness of the data. Missing data can be categorized into long-term and short-term missing data based on existing samples [24]. Data missing for five occurrences can be interpreted as a period during which the onboard equipment experienced a connection interruption or had part of the data deleted, while other missing data can be treated as short-term missing data. For short-term missing data, a weighted moving average is utilized for data processing.

Weighted sliding has the advantage of simplicity and ease of use and has a wide range of applications in non-stationary data processing compared to other methods. Using the weighted sliding average method for missing data, each missing data value is supplemented by the weighted average of k observations on both sides, i.e., it is the sliding window that is used, and if $\{Y_t, t = 1, \cdots, T\}$ is used to represent the target time data series, the sliding weighted average computational expression can be obtained as follows:

$$\hat{Y}_{t+1} = \sum_{i=-k}^{k} \omega_i Y_{t+1+i}, i \neq 0 \tag{15}$$

In Equation (15), $\omega_{-k}, \omega_{-k+1}, \cdots, \omega_k$ represents the weight of each point of the sample in the processed data.

Vehicle-mounted equipment in the existence of another problem is the existence of outliers in the vehicle-mounted equipment data. If you can better deal with the outliers, it will directly affect the analysis of the state of the vehicle-mounted equipment, combined with the characteristics of real-time data of the vehicle-mounted equipment and the design of the use of the box diagram method to deal with the outliers of the vehicle-mounted equipment data.

The box plot can be divided into the lower edge, the upper quartile, median, lower quartile, and upper edge of the five parts, in which the middle of the box for the box, the box of the median position that is the median, on behalf of the analyzed data series in the median, the box of the upper end of the quartile, and the lower end of the quartile were used to Q_3 and Q_1 said that, the lower end of the quartile Q_1 to the upper end of the quartile Q_3 distance is the sub-distant distance, the use of IQR said that. The method of data outlier handling using box plots can be divided into the following steps:

1. Enter the data that need to be processed containing outliers $x_i, i = 1, 2, \cdots, n$;
2. The upper and lower quartiles of the confirmatory box type, where the quartile distance IQR is calculated as follows:

$$IQR = Q_3 - Q_1 \tag{16}$$

3. Assuming the parameter $k = 1.5$, the upper quartile $B_1(k)$ and the lower quartile $B_2(k)$ of the box type are calculated as follows [25,26]:

$$B_1(k) = Q_3 + k \cdot IQR \tag{17}$$

$$B_2(k) = Q_1 - k \cdot IQR \tag{18}$$

4. Assume that the parameters $k = 3$, $B_1(k)$ and $B_2(k)$ represent the upper and lower edges of the box plot, respectively;
5. If the data x_i are mild outliers when the data $x_i \in [B_1(1.5), B_1(3)]$ or $x_i \in [B_2(3), B_2(1.5)]$ are used, it can be determined;
6. If x_i is an extreme outlier in the data sequence when the data $x_i \in [B_1(3), \infty]$ or $x_i \in [-\infty, B_2(3)]$ is available, then it is an extreme outlier in the data sequence;
7. The outliers in the data series are eliminated based on the box plot.

After processing the missing data and outliers, the data features are fused using the Gaussian mixture model (GMM) [27]. For the in-vehicle equipment data, they are viewed as a series of individually Gaussian-distributed data mixtures, which can characterize the complex in-vehicle equipment data. A single Gaussian fit to the data scatter is shown in Figure 2.

It can be seen that by fitting the distribution with a single Gaussian, the scatters are divided into two categories, which are randomly generated from two different normal distributions, and it is difficult to fit these scatters using a single Gaussian. Based on the single Gaussian fit, a mixture model using a double Gaussian distribution is able to fit these scatters, as shown in Figure 3.

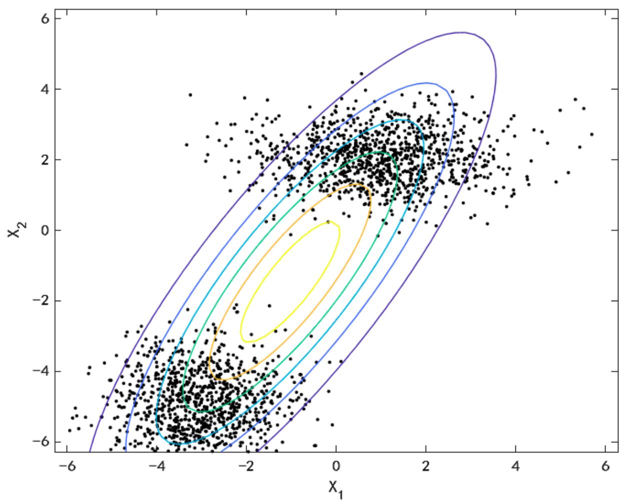

Figure 2. Scatter distribution of single Gaussian fit data.

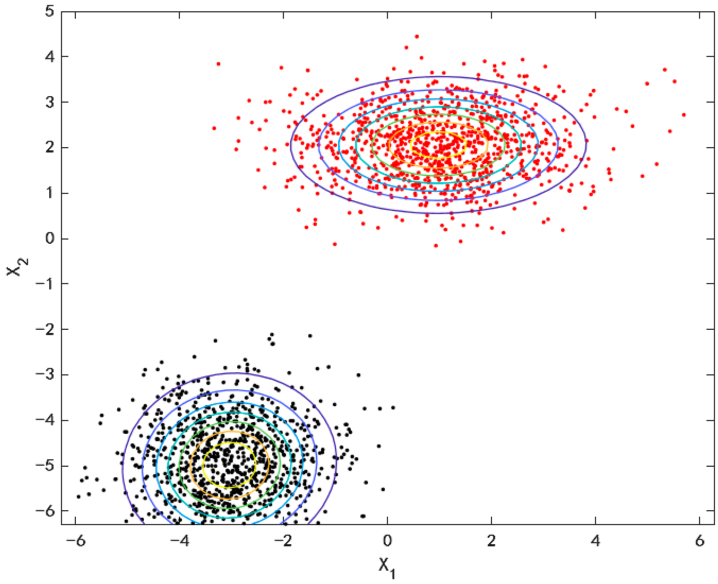

Figure 3. Gaussian mixture model fitted data scatter distribution.

In order to be able to process the data using a Gaussian mixture model, a schematic of the Gaussian mixture distribution used is shown in Figure 4.

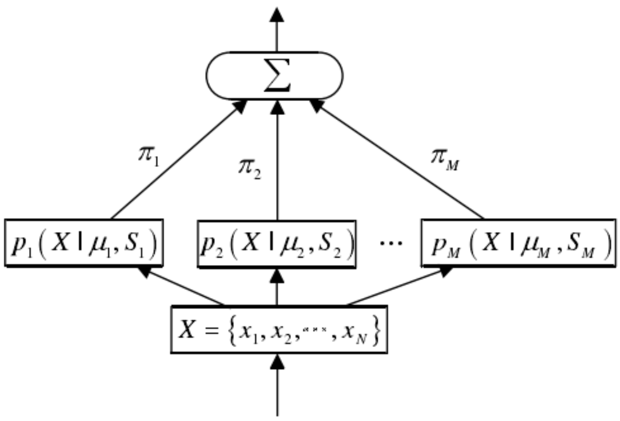

Figure 4. Schematic diagram of Gaussian mixture model.

4. Real-Time Data Cleaning and Preprocessing Algorithm

4.1. Data Cleaning and Preprocessing Method for Onboard ETC

The data in onboard ETC mainly consist of sensor data and communication information data. According to the characteristics of onboard sensor data, real-time data are processed based on different cleaning stages and varying data type features. A mixed cleaning process is applied to the entire real-time data from onboard equipment, employing methods such as the Reinhardt criterion method and the moving average filtering method [28–30].

1. Reinhardt Criterion Method: The Reinhardt criterion is used to judge gross errors based on a given confidence probability (usually 99.7%). It utilizes three times the standard deviation of the collected data as a reference. Any error exceeding this standard is considered a gross error rather than a random error. Data containing gross errors are termed abnormal data, or outliers, and should be removed from the collected data [31].

For the data captured in the ETC $x_1, x_2, x_3, \cdots, x_n$, the arithmetic mean can be calculated for it as follows:

$$\overline{x} = \frac{1}{n\sum_{i=1}^{n} x_i} \tag{19}$$

The error of the ETC collection data is calculated as follows:

$$\nu_i = x_i - \overline{x} \tag{20}$$

Using Bessel's formula, you can calculate σ as the following:

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n} \nu_i^2} \tag{21}$$

If the collected data $|x_i - \overline{x}| > 3\sigma$, then the data collected by ETC x_i are abnormal data, and take the rejection processing, if the collected data $|x_i - \overline{x}| \leq 3\sigma$, then the data collected by ETC x_i are normal data, as the basis data of the state evaluation of the vehicle equipment [32].

2. Sliding Average Filtering Method: Sliding average filtering is the collected N data in chronological order, seen as a queue, we called this queue a window, the length of the queue is fixed as N every new data collection, and the sampling value into the end of the queue, and we remove the original queue head of a data so that the queue always has N "latest" data, and then find the average value of the N latest data, and then we find the average value of the N latest data. Then we find the average value of these N latest data [33]. The arithmetic formula used is as follows:

$$\overline{x}_n = \frac{1}{N}\sum_{i=0}^{N-1} x_{n-i} \tag{22}$$

In Equation (22), $\overline{x}_n$ represents the filtered output of the n st ETC sample, x_{n-i} represents the value of the $n-i$th sample that has not been passed, and N represents the number of sliding average terms.

4.2. CPC Data Cleaning and Preprocessing Algorithm

Onboard CPC data generated need to be cleaned and analyzed in real time to provide timely and accurate data for the assessment of onboard equipment. Continuous real-time data collection from the onboard system requires real-time cleaning. This necessitates a sliding window to process the collected current data within the window for any data errors, data loss, random errors, and noise data. The framework for the real-time cleaning preprocessing algorithm is illustrated in Figure 5.

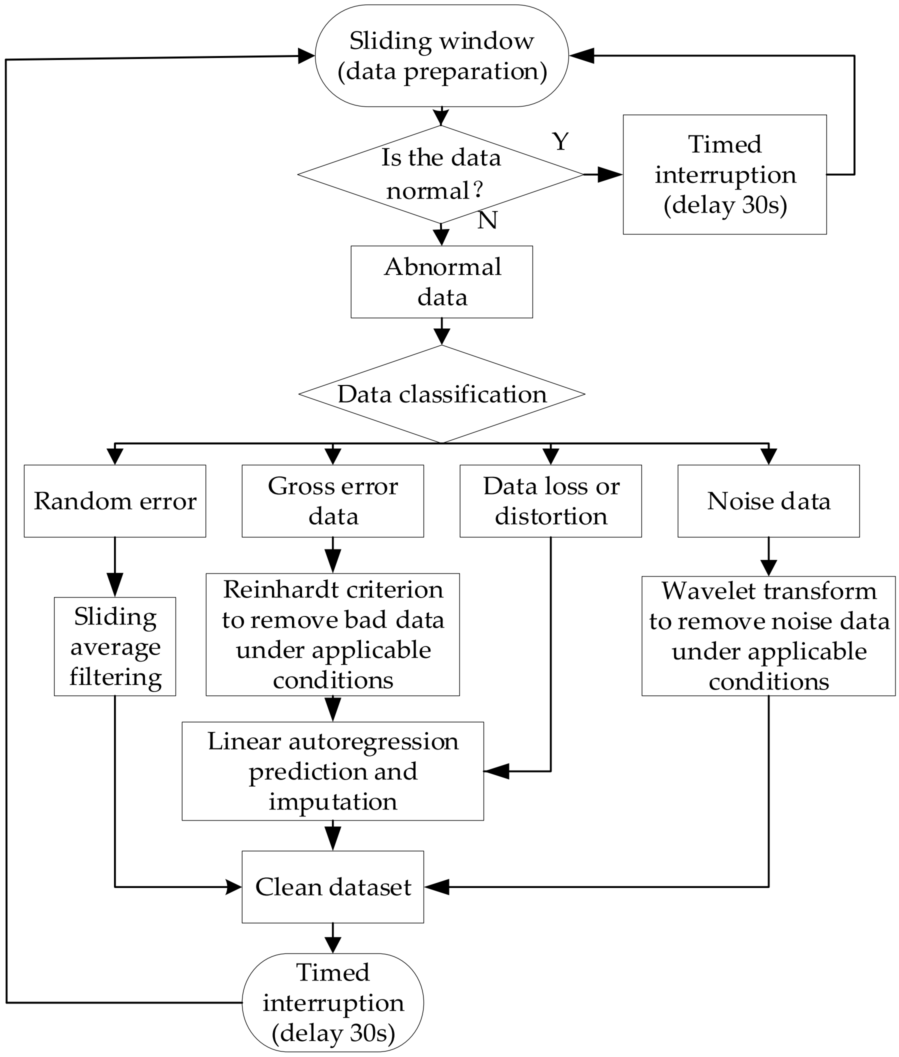

Figure 5. Structure of real-time cleaning algorithm for in-vehicle CPC continuous type data.

5. Establishment of the Onboard Equipment Status Evaluation Index System

5.1. Construction of the Index System

Based on the analysis of existing onboard equipment data and state variables, the onboard equipment status evaluation system is constructed from the aspects of accuracy, reliability, component configuration, operational environment, and safety of the equipment [34,35]. The analytic hierarchy process (AHP) is used to determine the subjective weights of the evaluation system, while the entropy–weight–coefficient of variation method is used to determine the objective weights of the evaluation indicators, enhancing the accuracy of each indicator within the evaluation system. The construction process of the onboard equipment status evaluation index system is illustrated in Figure 6.

Based on the technical specifications of the currently configured vehicle equipment and the hierarchical structure, a three-level indicator system was constructed, consisting of a goal layer, a criterion layer, and a factor layer. According to the established vehicle status assessment indicator system structure, the second-level criterion layer mainly includes the accuracy, reliability, component configuration [36], operating environment of the vehicle equipment, equipment safety, etc. Furthermore, each criterion layer is further refined, resulting in corresponding factor layer indicators.

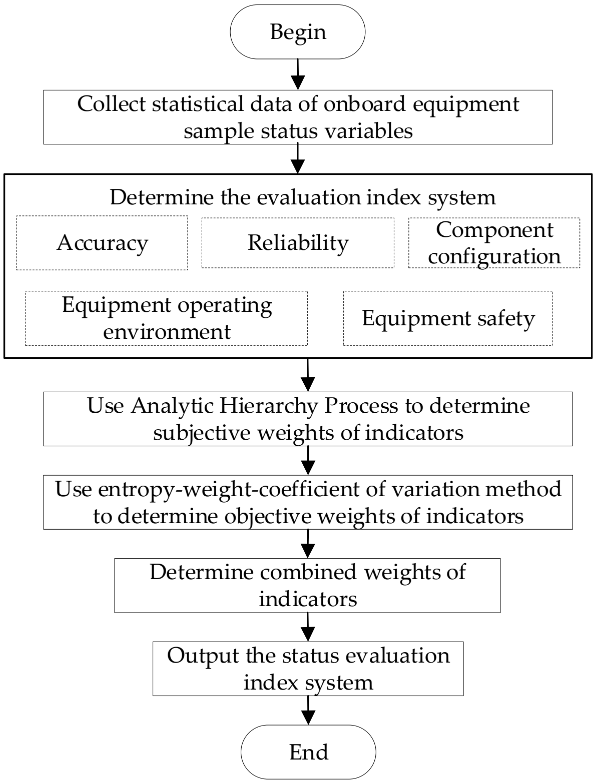

Figure 6. Flow of constructing onboard equipment condition assessment index system.

5.2. Main Indicator Analysis

- Accuracy Indicators

Accuracy indicators U_1 mainly include evaluation errors of onboard equipment U_{11}, functional modules U_{12}, operational errors U_{13}, and communication errors U_{14}.

The evaluation error is calculated based on the relationship between the measured value and the evaluated value of the onboard equipment [37]. The evaluation reference standards specify accuracy grade requirements for different vehicle evaluation errors. The functional modules of onboard equipment mainly include the power module, data acquisition module, collection module, main control module, communication module, and data storage module, among others. The normal functioning of these modules can be determined in conjunction with the factory indicators of the devices, allowing maintenance personnel to assess the status of each module.

- Reliability Indicators

Reliability indicators U_2 mainly consider family defects U_{21} and operational time index U_{22} within the evaluation index system for the status of onboard equipment. If there are family defects in the onboard equipment, it will not only lead to errors in the status evaluation but also affect the normal operation of the entire ETC system and equipment. When constructing the status evaluation index, it is necessary to consider the family defect records from the manufacturer of the onboard equipment and determine the corresponding scores. Onboard equipment consists of many electronic components, and the accumulation of operation time increases the likelihood of failure, thereby reducing the service life.

- Component Configuration

Component configuration U_3 mainly includes integrity U_{31}, communication errors U_{32}, and qualification rate of the components U_{33}. Integrity refers to the completeness and damage of key devices such as the onboard equipment connection box and signal input/output, which can be judged by maintenance personnel. The wiring requirements for onboard equipment are high; different wiring methods correspond to different usage methods. If there are wiring errors in the onboard equipment, it will directly affect the operational reliability of the equipment [38].

- Equipment Operating Environment

The equipment operating environment U_4 mainly includes temperature U_{41}, relative humidity U_{42}, and electromagnetic compatibility in the working environment of the onboard equipment U_{43}. The temperature and humidity in the equipment operating environment can affect the performance and service life of the electronic components that make up the onboard equipment, as well as the insulation performance of precision electronic devices and communication devices within the equipment [39]. The electromagnetic compatibility of onboard equipment is assessed through resistance to electromagnetic interference and suppression of radio interference, which mainly includes electrostatic discharge, radio frequency electromagnetic fields, electrical fast transients, and surge voltage in the equipment.

- Safety Requirements

Safety requirements U_5 mainly include communication safety U_{51}, electrical safety U_{52}, and operational parameters U_{53}. According to the general technical specifications for vehicle equipment, specific size requirements for device operational parameters need to meet regulatory requirements and conform to national standards for vehicle equipment operation.

6. Based on Analytic Hierarchy Process–Entropy Weight–Coefficient of Variation Method for Determining Indicator Weights

6.1. Analytic Hierarchy Process–Entropy Weight–Coefficient of Variation Method Analysis

The subjective weights of indicators evaluated by the analytic hierarchy process (AHP) are determined by inviting experts to score the indicators in the index system, obtaining the relative importance of the elements in the index system through pairwise comparisons. This allows for the determination of subjective weights by establishing each expert's original A-U judgment matrix X.

$$X = \begin{bmatrix} 1 & \frac{1}{2} & 3 & \frac{1}{3} & 2 \\ 2 & 1 & 3 & \frac{1}{2} & 3 \\ \frac{1}{3} & \frac{1}{3} & 1 & \frac{1}{3} & 2 \\ 3 & 2 & 3 & 1 & 4 \\ \frac{1}{2} & \frac{1}{3} & \frac{1}{2} & \frac{1}{4} & 1 \end{bmatrix} \tag{23}$$

We perform consistency checks on the judgment matrix; the calculation formula for consistency verification is as follows:

$$CR = \frac{CI}{RI} \tag{24}$$

In Equation (24), the CI indicators used for verification are calculated as follows:

$$CI = \frac{\lambda_{\max} - n}{n-1} \tag{25}$$

In Equation (25), $\lambda_{\max}$ is the largest eigenvalue of the judgment matrix, and the only non-zero eigenroot for the n order consistency matrix is n, and the judgment matrix is a consistency matrix if and only if $\lambda_{\max} = n$. The consistency metric CR is calculated using the stochasticity metric RI numerical table and the stochasticity metric RI numerical table is shown in Table 5.

Table 5. Indicators of stochasticity RI table of values.

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.52	0.89	1.12	1.26	1.36	1.41	1.46	1.49

The consistency ratio $CR < 0.1$ can be obtained through the calculation, which meets the consistency test requirements, and the obtained feature vector can be used as the vector of weights, and the corresponding value is the indicator weight value.

The objective weights of the evaluation indicators of the entropy weighting method are obtained by normalizing the original matrix $X = (x_{ij})_{m \times n}$ to obtain the planning matrix $Z = (z_{ij})_{m \times n}$; x_{ij} represents the original values of the indicators for the i sample scenario and the j indicator.

The homogenization of the indicators gives the value of the weighting of the i program indicator under the j indicator:

$$r_{ij} = \frac{z_{ij}}{\sum\limits_{i=1}^{n} z_{ij}} \tag{26}$$

The entropy value of the indicators in the evaluation system is as follows:

$$s_j = -\frac{1}{\ln m} \sum_{i=1}^{m} r_{ij} \ln r_{ij} \tag{27}$$

In order to use the entropy value for the calculation of indicator weights, a coefficient of variation c_j is defined as follows:

$$c_j = 1 - s_j \tag{28}$$

Based on the entropy value the objective weights of the indicators q_j can be calculated as follows:

$$q_j = \frac{c_j}{n - \sum\limits_{j=1}^{n} s_j} \tag{29}$$

The coefficient of variation method relies on the information contained in the indicator data to solve the weights and judges the degree of difficulty in achieving the indicators according to the size of the difference between the indicators. Due to the wide variety of indicators involved in the evaluation system, each indicator has a different outline, and it is not possible to directly compare the indicators in the indicator system, so it is possible to use the coefficient of variation method to carry out a dimensionless processing and compare the differences between the indicators. Using the coefficient of variation method to solve the method, assuming that there are m evaluation samples and n evaluation indicators to deal with, the original data for $X = (x_{ij})_{m \times n}$, x_{ij} represent the i sample program of the j indicators of the original value, using the normalization process to obtain:

$$z_{ij} = \frac{x_{ij}}{\sum\limits_{i=1}^{n} x_{ij}} \tag{30}$$

Based on the obtained subjective and objective weights of the indicators it is possible to determine the value of the combined weights of the indicators Q_i for the following:

$$Q_i = \beta q_i' + (1 - \beta) q_i'' \tag{31}$$

In Equation (31), q_i' and q_i'' represent subjective and objective weights respectively, subjective weights are subjective weights determined by comprehensive hierarchical analysis, objective weights are objective weights determined by entropy weights, and β is the coefficient of subjective weights, which is taken in conjunction with the relevant requirements of each indicator in the assessment of the health status of actual vehicle-mounted equipment, and the range of the value is (0, 1).

6.2. Indicator Weight Determination

Indicator U_{ij} is the value of the second level indicator j under the first level indicator i and is calculated by adding the values of the subordinate indicators it contains, as follows:

$$U_{ij} = \sum y_j \tag{32}$$

In Equation (32), $i = 1, 2, 3, 4, 5$, $j = 1, 2, 3, 4$.

U_i is the value of the i first level indicator, which is obtained by multiplying the value of the third level indicator to which it belongs by its respective weight, and then summing it up, which is calculated as follows:

$$U_i = \sum y_i w_j \tag{33}$$

Equation (33) in which y_i is the value of the tertiary indicator, w_j the weight of a tertiary indicator under the primary indicator, which is obtained by calculating the weight of the primary indicator.

Five experts were used to determine the relationship and relative importance of the indicator layers through subjective evaluation and then determine the weight coefficients, and the objective coefficients were obtained by using the entropy weighting method and statistically calculated based on the expert scoring of each level and the data obtained from the entropy weighting method for each indicator.

7. Determination of Onboard Equipment Health Status Indicator Weights Case Analysis

7.1. Determination of Subjective Weights (ANP)

The analytic network process (ANP) is applied to determine the subjective weights of the indicators. It is assumed that there are elements in the control layer of the ANP $P_1, \cdots, P_n$, and there are groups of elements in the network layer $C_1, \cdots, C_n$. The elements in the control layer serve as criteria, and AHP scoring is used for scaling, as shown in Table 6.

Table 6. Specific meaning table of ANP scoring scale.

Judgment Scale	Scoring Definition
1	Element A is equally important as Element B
3	Element A is slightly more important than Element B
5	Element A is moderately more important than Element B
7	Element A is much more important than Element B
9	Element A is absolutely more important than Element B
2, 4, 6, 8	Intermediate importance between the two adjacent judgments

In order to be able to ensure the consistency of the judgment matrix, the consistency ratio is used for testing, which is $CR = CI/RI$, for testing the randomness of the expert scoring. According to the expert scoring in the hierarchical analysis method, six experts were invited to score the scores, and the scoring results of some indicators obtained are shown in Table 7.

The subjective weight matrix of expert ratings can be obtained as U_c = {0.15 0.28 0.11 0.30 0.16}.

The subjective weighting scoring of the factor level indicators in the obtained measurement accuracy indicator U_1 is constructed to obtain a judgment matrix as shown in Table 8.

Table 7. Indicator scoring table.

Evaluation Indicators	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6
Accuracy	6	5	5	4	6	6
Dependability	9	9	8	9	8	9
Component configuration	3	2	3	3	2	3
Vehicle-mounted equipment operating environment	9	9	9	9	9	9
Safety	7	6	5	6	5	5

Table 8. Judgment matrix for accuracy indicator.

A_{U_1}	Assessment Error U_{11}	Functional Module U_{12}	Running Error U_{13}	Communications Error U_{14}
assessment error U_{11}	(1, 1, 1)	(1, 2, 3)	(3/2, 5/2, 7/2)	(2, 3, 4)
functional module U_{12}	(1/3, 1/2, 1)	(1, 1, 1)	(1/2, 3/2, 5/2)	(1, 2, 3)
running error U_{13}	(2/7, 2/5, 2/3)	(2/5, 2/3, 2)	(1, 1, 1)	(1/2, 3/2, 5/2)
communications error U_{14}	(1/4, 1/3, 1/2)	(1/3, 1/2, 1)	(2/5, 2/3, 2)	(1, 1, 1)

According to Equations (10) and (11) can be obtained $CI = 0.0057$, $CR = 0.004$, meet $CR < 0.1$, meet the consistency requirements, can be used to measure the accuracy of the indicator U_1 judgment matrix for weight calculation. The subjective weights of the indicators $q'_{11} = 0.43$, $q'_{12} = 0.25$, $q'_{13} = 0.20$, $q'_{14} = 0.14$ can be obtained.

7.2. Determination of Objective Indicator Weights

The obtained sample indicators of the factor stratum were subjected to data operations based on the coefficient of variation method, and the equations and means in the obtained sample indicators were obtained with the coefficient of variation $V_i = \frac{\sigma_i}{x_i}$, where i represents all the samples of indicators in the indicator.

The use of expert bias coefficients can determine the weight of the indicators in the guideline layer, but the indicators in the factor layer need to be combined with the actual operation of the onboard equipment status data for statistics, to statistics obtained by the onboard equipment accuracy indicators U_1 as an example of the analysis, the sample data classification and organization of the use of the formula $u'_{ijh} = \frac{u_{ijh} - u_{ij\min}}{u_{ij\max} - u_{ij\min}}$ for quantification, you can obtain the quantification of the state of the onboard equipment quantitative data shown in Table 9.

Based on the quantification of the fundamental data obtained, the results obtained are substituted into the weight coefficients, the expert bias coefficients are taken as 0.5, and the objective weights are used to calculate the combined weights $q''_{11} = 0.46$, $q''_{12} = 0.19$, $q''_{13} = 0.22$, and $q''_{14} = 0.17$. The combined weights for the accuracy of the onboard equipment can be obtained $Q_{11} = 0.445$, $Q_{12} = 0.22$, $Q_{13} = 0.21$, and $Q_{14} = 0.155$.

Using this method to calculate other factor layer indicators in the condition assessment index system of vehicle-mounted equipment, we can obtain the weights of vehicle-mounted equipment indicators as shown in Table 10.

Table 9. Equipment assessment accuracy metrics U_1 sample data quantification table.

Sample Data Number	Assessment Error U_{11}	Functional Module U_{12}	Running Error U_{13}	Communications Error U_{14}
1	(0.1/0.75)	(1/1)	(0.25/0.75)	(1/1)
2	(1.25/0.63)	(0.1/0.30)	(0.30/0.60)	(1/1)
3	(0.1/0.75)	(0.8/0.70)	(0.25/0.65)	(1/1)
4	(0.1/0.80)	(1/1)	(0.20/0.80)	(0.60/0.0)
5	(0.15/0.44)	(0.65/0.35)	(0.22/0.77)	(1/1)
6	(0.10/0.75)	(1/1)	(0.15/0.90)	(0.80/0.50)
7	(0.18/0.32)	(0.80/0.70)	(0.25/0.70)	(0.7/0.30)
8	(0.25/0)	(0.80/0.65)	(0.25/0.55)	(1/1)
9	(0.05/0.88)	(1/1)	(0.20/0.85)	(0.80/0.65)
10	(0.11/0.85)	(1/1)	(0.15/0.75)	(1/1)
11	(0.15/0.55)	(0.80/0.10)	(0.25/0.80)	(0.50/0.20)
12	(0.15/0.60)	(1/1)	(0.30/0.85)	(1/1)
13	(0.15/0.50)	(1/1)	(0.15/0.90)	(0.70/0.65)
14	(0.15/0.60)	(0.75/0.45)	(0.30/0.90)	(0.5/0.15)
15	(0.30/0)	(0.1/0.75)	(0.1/0.75)	(0.1/0.75)
16	(0.15/0.40)	(1/1)	(0.25/0.15)	(1/1)
17	(0.20/0.25)	(0.65/0)	(0.50/0)	(1/1)
18	(0.25/0)	(0.85/0)	(0.40/0.55)	(0.65/0.35)
19	(0.10/1)	(1/1)	(0.45/0.55)	(0.70/0.35)
20	(0.15/0.45)	(1/1)	(0.25/1)	(1/1)

Table 10. Indicator weights for the onboard equipment factor layer.

Norm	Subjective Weighting	Objective Weighting	Combined Weighting of This Research
assessment error U_{11}	0.43	0.46	0.445
functional module U_{12}	0.25	0.19	0.22
running error U_{13}	0.20	0.22	0.21
communications error U_{14}	0.14	0.17	0.155
family flaw U_{21}	0.325	0.553	0.44
running time index U_{22}	0.58	0.47	0.525
encapsulation U_{31}	0.335	0.37	0.353
communications error U_{32}	0.48	0.415	0.45
composition pass rate U_{33}	0.21	0.285	0.25
temp U_{41}	0.552	0.28	0.42
relative humidity U_{42}	0.285	0.332	0.31
electromagnetic compatibility U_{43}	0.215	0.340	0.278
communications sec urity U_{51}	0.18	0.355	0.268
electrical safety U_{52}	0.315	0.355	0.335
operating parameters U_{53}	0.485	0.355	0.42

7.3. Determination of Comprehensive Weights for Indicators Based on Hierarchical Analysis–Entropy Weight–Coefficient of Variation Method

The scoring by experts on the criterion layer indicators is uniformly quantified, resulting in the processed criterion layer indicators as shown in Table 11.

Table 11. Expert score table for criterion layer indicators.

A_U	U_1	U_2	U_3	U_4	U_5
U_1	(1, 1, 1)	(1, 2, 2)	(1, 3, 2)	(1, 2, 3)	(1, 1, 1)
U_2	(1/2, 1/3, 1)	(1, 2, 1)	(1, 1, 2)	(2, 1, 3)	(2, 1, 1)
U_3	(1/2, 1/3, 1/2)	(1/3, 1/2, 1/3)	(1, 1, 1)	(1, 1, 2)	(1/2, 1/2, 1)
U_4	(1/2, 1/2, 1/3)	(1/2, 1/3, 1/2)	(1, 1/2, 1)	(2, 1, 1)	(1/2, 1, 1/2)
U_5	(1, 1/2, 1)	(1, 1, 1)	(1, 2, 1)	(2, 1, 1)	(1, 2, 1)

Based on the processed expert ratings, the subjective weights of the in-vehicle equipment criterion layer can be obtained through the rating judgment matrix $q_1' = 0.38$, $q_2' = 0.23$, $q_3' = 0.17$, $q_4' = 0.11$, and $q_5' = 0.11$.

Based on the calculated medium and objective indicators in the factor layer, the entropy weighting method was introduced into the correction of the objective indicator weights in the criterion layer, and the obtained indicator weights in the criterion layer of the onboard equipment are shown in Table 12.

According to the obtained health state evaluation indexes of vehicle-mounted equipment, it is known that the comprehensive weights of the indexes obtained by using the hierarchical–entropy weights–coefficient of variation method are between subjective weights and objective weights, and the comprehensive weight indexes can combine the advantages of experts' experience and the objectivity of the actual operation data, which proves the superiority of the obtained comprehensive weights.

Table 12. Indicator weights for the in-vehicle equipment guideline layer.

Normative Level Indicators	Subjective Weighting	Objective Weighting	Combined Weights After Correction of This Research
U_1	0.38	0.33	0.355
U_2	0.23	0.25	0.24
U_3	0.17	0.15	0.16
U_4	0.11	0.13	0.12
U_5	0.11	0.14	0.125

8. Conclusions

This research provides an in-depth discussion on in-vehicle real-time data analysis and health state assessment with the aim of constructing a health state assessment index system based on multi-source data fusion to cope with the needs of modern technological development, especially to fill the gaps in the traditional assessment methods in the application of non-stop toll collection system (ETC) and other complex vehicle management applications.

The novelty of this research is mainly reflected in the following aspects:

Application of multi-source data fusion technology: This research synthesizes multiple data sources to improve the comprehensiveness and objectivity of the assessment. This systematic framework has not been fully emphasized in current related research, thus enhancing the equipment condition monitoring capability.

Innovation of comprehensive assessment method: Combining advanced assessment methods such as hierarchical analysis, fuzzy comprehensive judgment method, entropy value method, and Delphi method makes the assessment of the health status of vehicle-mounted equipment more scientific and comprehensive, which presents obvious advantages compared with the recent research work.

In-depth analysis of failure rate: The simulation of equipment failure using the Weibull distribution model provides a new perspective for understanding the potential risks of equipment in long-term use, and this analysis is the first of its kind in the related literature, demonstrating methodological and theoretical innovations.

Despite the positive results of this research, certain limitations still exist. First, the selection of the research sample may affect the generalizability of the results. Future studies should consider a wider range of sample types, such as different makes and models of vehicles, to enhance model adaptability. Second, most of the current studies focus on data analysis and model construction, and the validation of practical applications is still relatively limited. Therefore, subsequent studies can focus on testing and applying this assessment model in real environments to verify its effectiveness and operability. Finally, with the development of artificial intelligence and big data technology, future research can explore the use of more advanced machine learning and deep learning algorithms to improve the accuracy of cleaning and analyzing data and the comprehensiveness of the assessment.

In summary, this research provides a new methodological foundation for health state assessment of in-vehicle equipment and points the way for future research. By continuing to explore and address the existing limitations, it can further promote the development of this field while enhancing the management and operational efficiency of modern transportation systems.

Author Contributions: Conceptualization, F.Z., T.Y. and F.G.; methodology, F.Z. and T.Y.; software, T.Y.; validation, F.Z., T.Y. and F.G.; formal analysis, T.Y.; investigation, F.Z., T.Y. and F.G.; resources, F.Z. and F.G.; data curation, T.Y.; writing—original draft preparation, T.Y.; writing—review and editing, F.Z., T.Y. and F.G.; visualization, T.Y.; supervision, F.Z. and F.G.; project administration, F.Z., T.Y. and F.G.; funding acquisition, F.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This work is partially supported by the Renewable Energy Technology Research institution of Fujian University of Technology Ningde, China (funding number: KY310338); the 2020 Fujian Province "Belt and Road" Technology Innovation Platform (funding number: 2020D002); the Provincial Candidates for the Hundred, Thousand and Ten Thousand Talent of Fujian (funding number: GY-Z19113); the Patent Grant project (funding numbers: GY-Z18081, GY-Z19099, and GY-Z20074); Horizontal projects (funding number: GY-H-20077); the municipal-level science and technology projects (funding numbers: GY-Z-22006 and GY-Z-220230); the Fujian Provincial Department of Science and Technology Foreign Cooperation Project (funding number: 2023I0024); and the Open Fund project (funding numbers: KF-X19002 and KF-19-22001).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The ETC transaction data utilized in this study were obtained from Fujian Expressway Information Technology Co., Ltd., Fu Zhou, China. Restrictions apply to the availability of these data, which were used under license for this study and are not publicly available. Data are available from the authors with the permission of Fujian Expressway Information Technology Co., Ltd. All data processing and analyses were conducted in compliance with relevant data protection and privacy laws. No individual or personal data were used in this study.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Cai, D. Research on Operation and Maintenance Management of Highway ETC Gantry System. *Transp. Manag. World* **2023**, *7*, 118–120.
2. Wu, H. Exploration of Intelligent Operation and Maintenance Management System for Highway Electromechanical Systems. *China Transp. Inf.* **2024**, *2*, 127–129.
3. Luo, Z. Intelligent Operation and Maintenance System for ETC Gantry Electromechanical Equipment Based on Data Quality Monitoring. *China Transp. Inf.* **2023**, *7*, 142–145.
4. Yang, X.; Wang, X.K.; Hu, H.; Zhu, M. A Review of Visualization Technologies for Equipment Status Monitoring. *Comput. Sci.* **2022**, *49*, 89–99.
5. Qian, M. Analysis of Multi-dimensional Data Fusion and Application of ETC Portal System. *China ITS J.* **2021**, *6*, 109–112.
6. Huang, X.; Zhang, X.; Xiong, Y.; Dai, F.; Zhang, Y. Intelligent Fault Diagnosis of Turbine Blade Cracks via Multiscale Sparse Filtering and Multi-kernel Support Vector Machine for Information Fusion. *Adv. Eng. Inform.* **2023**, *56*, 101979. [CrossRef]
7. Guo, J.; He, Q.; Zhen, D.; Gu, F.; Ball, A.D. Multi-sensor Data Fusion for Rotating Machinery Fault Detection Using Improved Cyclic Spectral Covariance Matrix and Motor Current Signal Analysis. *Reliab. Eng. Syst. Saf.* **2023**, *230*, 108969. [CrossRef]
8. Zhang, P.; Chen, C. A Two-Stage Framework for Time-Frequency Analysis and Fault Diagnosis of Planetary Gearboxes. *Appl. Sci.* **2023**, *13*, 5202. [CrossRef]
9. Li, W.; Qiu, M.; Zhu, Z.; Wu, B.; Zhou, G. Bearing Fault Diagnosis Based on Spectrum Images of Vibration Signals. *Meas. Sci. Technol.* **2016**, *27*, 035005. [CrossRef]

10. Liang, Y.; Zhang, Y.Y.; Gong, M.; Ren, M.; Cheng, L. Fault Detection Method Based on Generalized Mutual Entropy Principal Component Analysis. *J. Taiyuan Univ. Technol.* **2020**, *51*, 438–445.
11. Shao, Y.; Wu, J.W.; Ma, S.; Chang, Y.; Feng, Y.; Yang, N.; Li, D. AM-ReliefF Feature Selection Based Integrated SVM Method for Mechanical Fault Diagnosis of High Voltage Circuit Breakers. *Proc. Chin. Soc. Electr. Eng.* **2021**, *41*, 2890–2901.
12. Michal, K.; Peráček, T. Synergies and Potential of Industry 4.0 and Automated Vehicles in Smart City Infrastructure. *Appl. Sci.* **2024**, *14*, 3575. [CrossRef]
13. Peng, L.; Dang, S.L.; Ouyang, H.; Li, J.; Zhao, J. Group Equipment Warning Based on Convolutional Long Short-Term Memory Networks. *Control Eng.* **2022**, *29*, 551–557.
14. Yang, J.; Wan, A.P.; Wang, J.; Shan, T.; Miao, X.; Li, K.; Zuo, Q. Bearing Fault Diagnosis of Aero-Engines Based on Multi-sensor Fusion Convolutional Neural Networks. *Zhejiang Univ.* **2022**, *42*, 4933–4942.
15. Liu, J. Research on Real-time Anomaly Detection of Urban Rail Transit Train Operation Speed Based on XGBoost Model. *J. Chongqing Jiaotong Univ. (Nat. Sci. Ed.)* **2021**, *40*, 49.
16. Zhang, J.L.; Li, Y.; Zhu, C.S.; Xue, H.; Ma, J.; Zhang, L.; Bi, S. Fault Warning Method for Substation Equipment Based on Dual-domain Sparse Transformer. *Comput. Sci.* **2024**, *3*, 1–10.
17. Rastislav, F. Automated Driving and Data Protection: Some Remarks on Fundamental Rights and Privacy. *Kryt. Prawa* **2021**, *13*, 106–118.
18. Zhou, Y.; Balbir, S.D. Research on comprehensive evaluation of health status of mechanical equipment with multi-feature parameters based on Fuzzy-AHP. *China Mech. Eng.* **2009**, *20*, 2487–2492.
19. Zou, F.; Ren, Q.; Tian, J.; Guo, F.; Huang, S.; Liao, L.; Wu, J. Expressway Speed Prediction Based on Electronic Toll Collection Data. *Electronics* **2022**, *11*, 1613. [CrossRef]
20. Sankar, A.; Wu, Y.; Gou, L.; Zhang, W.; Yang, H. Dysat: Deep neural representation learning on dynamic graphs via self-attention networks. In Proceedings of the 13th International Conference on Web Search and Data Mining, Houston, TX, USA, 3–7 February 2020; pp. 519–527.
21. Chang, C.C.; Lin, C.J. LIBSVM: A library for support vector machines. *ACM Trans. Intell. Syst. Technol.* **2011**, *2*, 1–27. [CrossRef]
22. Wang, K.; Zhou, Z.C.; Qu, K.; Cao, S.; Hu, Y. Track prediction based on CNN-LSTM model with attention mechanism. *J. Air Force Eng. Univ.* **2023**, *24*, 50–57.
23. Xu, X.; Qin, F.; Zhao, W.; Xu, D.; Wang, X.; Yang, X. Anomaly detection with GRU-based bi-autoencoder for industrial multimode processes. *Int. J. Control Autom. Syst.* **2022**, *20*, 1827–1840. [CrossRef]
24. Wen, Z.; Yuan, L.N.; Huang, W.; Huang, W.; Mo, J.; Feng, W. Node classification algorithm based on graph multilayer perceptron. *Guangxi Sci.* **2023**, *30*, 942–950.
25. Kan, C.H.; Mou, Z.H.; Wu, J.K. Data-driven anomaly detection and early warning problems. *Sci. Technol. Innov.* **2021**, 27–28. [CrossRef]
26. Zhang, T.; Yu, J.; Liao, B.; Yu, G.; Bi, X. Node classification method for social networks based on graph embedding and support vector machines. *Comput. Appl. Res.* **2021**, *38*, 2646–2650+2661.
27. Wu, L.; Zhang, S.; Chen, W.; Hao, X. Identification and correction of abnormal measurement data in power system based on graph convolutional network and gated recurrent unit. *Electr. Power Syst. Res.* **2023**, *224*, 109740. [CrossRef]
28. Li, S.; Zaidi, N.A.; Du, M.; Zhou, Z.; Zhang, H.; Li, G. Property graph representation learning for node classification. *Knowl. Inf. Syst.* **2024**, *66*, 237–265. [CrossRef]
29. Jin, T.; Dai, H.; Cao, L.; Zhang, B.; Huang, F.; Gao, Y.; Ji, R. Deepwalk-aware graph convolutional networks. *Sci. China Inf. Sci.* **2022**, *65*, 152104. [CrossRef]
30. Lin, Z. *Research on Intelligent Management Technology of Highway Electromechanical Equipment*; Chang'an University: Xi'an, China, 2019.
31. Men, C. Analysis of Management Issues and Optimization Methods for Highway Electromechanical Systems. *China High-Tech Innov.* **2023**, *6*, 62–64.
32. Wang, L. Design of Smart Monitoring System for Highway Electromechanical Equipment. *Eng. Technol. Innov. Dev.* **2023**, *1*, 82–84.
33. Zhang, J. Monitoring of Highway Tunnel Electromechanical Equipment Based on Optical Fiber Temperature Sensors. *Traffic Technol.* **2024**, *1*, 92–95.
34. Xu, H. Simulation of Wireless Monitoring Method for Operational Status of Highway Electromechanical Equipment. *Comput. Simul.* **2019**, *36*, 121–125.
35. Wang, Y.; Liu, Z.; Xu, J.; Yan, W. Heterogeneous Network Representation Learning Approach for Ethereum Identity Identification. *IEEE Trans. Comput. Soc. Syst.* **2023**, *10*, 890–899. [CrossRef]
36. Cai, L.; Chen, Z.; Luo, C.; Gui, J.; Ni, J.; Li, D.; Chen, H. Structural Temporal Graph Neural Networks for Anomaly Detection in Dynamic Graphs. In Proceedings of the 30th ACM International Conference on Information & Knowledge Management, Virtual Event, QLD, Australia, 1–5 November 2021; pp. 3747–3756. [CrossRef]
37. Wang, S.; Lei, Y.; Yang, B.; Li, X.; Shu, Y.; Lu, N. A Graph Neural Network-based Data Cleaning Method to Prevent Intelligent Fault Diagnosis from Data Contamination. *Eng. Appl. Artif. Intell.* **2023**, *126*, 107071. [CrossRef]

38. Duan, J.; Wang, S.; Zhang, P.; Zhu, E.; Hu, J.; Jin, H.; Liu, Y.; Dong, Z. Graph Anomaly Detection via Multi-scale Contrastive Learning Networks with Augmented View. *Proc. AAAI Conf. Artif. Intell.* **2023**, *37*, 7459–7467. [CrossRef]
39. Liu, Y.; Pan, S.; Wang, Y.G.; Xiong, F.; Wang, L.; Chen, Q.; Lee, V.C. Anomaly Detection in Dynamic Graphs via Transformer. *IEEE Trans. Knowl. Data Eng.* **2021**, *35*, 12081–12094. [CrossRef]