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DEVELOPMENT OF A MODEL FOR THE INTELLIGENT ASSESSMENT OF THE TECHNICAL CONDITION OF BUSES BASED ON RFID AND ON-BOARD DIAGNOSTIC DATA

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Abstract: The increasing complexity of modern public transportation systems requires intelligent approaches to monitoring and evaluating the technical condition of buses. Traditional maintenance practices are often based on scheduled inspections and predefined service intervals, which may fail to identify developing technical faults at an early stage. This study proposes an intelligent assessment model for evaluating the technical condition of buses by integrating Radio Frequency Identification (RFID) data with On-Board Diagnostics (OBD) information. RFID technology is used to identify buses, record operational events, and associate maintenance activities with individual vehicles, while OBD systems provide real-time information about engine parameters, diagnostic trouble codes, fuel consumption, temperature, voltage, and other technical indicators. The proposed model combines data acquisition, preprocessing, feature extraction, multimodal data fusion, machine learning-based classification, and technical condition scoring. A composite Technical Condition Index is introduced to categorize buses into normal, warning, and critical states. The model can support predictive maintenance, reduce unexpected failures, improve fleet availability, and enhance transportation safety. The proposed framework is particularly relevant to urban bus fleets undergoing digital transformation and can be adapted to intelligent transport systems in developing countries.

Keywords: RFID, On-Board Diagnostics, bus fleet, technical condition, intelligent assessment, machine learning, predictive maintenance, data fusion.

Introduction. Urban public transportation plays an important role in ensuring population mobility, reducing traffic congestion, and supporting sustainable economic development. Buses constitute one of the most widely used forms of public transportation because of their flexibility and relatively low operating costs. However, the reliability and safety of bus transportation strongly depend on the technical condition of vehicles and the effectiveness of maintenance management. Conventional vehicle maintenance is commonly performed according to predefined mileage, operating hours, or calendar-based intervals. Although preventive maintenance can reduce some types of failures, it does not always reflect the actual technical condition of a vehicle. Two buses with identical mileage may have substantially different technical conditions because of differences in driving patterns, traffic conditions, road quality, load, environmental temperature, and maintenance history. The development of intelligent transportation systems has created new opportunities for continuous monitoring of vehicle condition. Modern buses are equipped with electronic control units and diagnostic interfaces

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capable of generating large amounts of operational information. On-Board Diagnostics (OBD) systems can provide valuable information about engine operation, fault codes, coolant temperature, engine speed, vehicle speed, battery voltage, fuel-related parameters, and other indicators. At the same time, Radio Frequency Identification (RFID) technology can provide an efficient mechanism for automatic vehicle identification and event tracking. RFID tags installed on buses can be detected at depots, maintenance stations, inspection points, or designated control zones. This makes it possible to associate diagnostic information, maintenance operations, inspection results, and operational events with a specific vehicle. However, RFID and OBD technologies usually operate as separate information sources. The integration of these heterogeneous data sources can provide a more comprehensive representation of the technical condition of a bus. Therefore, the development of an intelligent model capable of combining identification, operational, diagnostic, and maintenance data represents an important research direction. The objective of this study is to develop a conceptual intelligent assessment model that integrates RFID and OBD data for automated evaluation of bus technical condition. The model aims to transform heterogeneous vehicle data into an interpretable technical condition score and classify buses according to their maintenance priority.

Literature Review. RFID is an automatic identification technology that uses radio-frequency signals to identify objects equipped with electronic tags. In transportation systems, RFID can be used for vehicle identification, access control, fleet tracking, maintenance registration, and automated recording of operational events. Compared with manual identification procedures, RFID-based identification can reduce data-entry errors and increase the speed of vehicle registration. In a bus depot, for example, an RFID reader can automatically identify a bus when it enters or leaves a maintenance zone. The resulting event can be connected to information about the vehicle's maintenance history and diagnostic condition. The main limitation of RFID is that it does not directly measure the mechanical or electronic condition of a vehicle. Its primary value lies in identification and event-context information. Therefore, RFID data become considerably more useful when combined with diagnostic and sensor information.

On-Board Diagnostics Data. OBD technology provides access to information generated by vehicle electronic control systems. Depending on the vehicle architecture and available parameters, OBD data may include engine speed, coolant temperature, intake parameters, fuel-related measurements, battery voltage, vehicle speed, and diagnostic trouble codes. Diagnostic trouble codes are particularly important because they indicate detected abnormalities in vehicle systems. However, individual fault codes do not necessarily provide a complete representation of the overall technical condition of a bus. A comprehensive assessment should consider the frequency of faults, persistence of abnormal parameters, operating conditions, historical maintenance information, and trends over time.

Machine Learning for Vehicle Condition Monitoring. Machine learning techniques have increasingly been applied to predictive maintenance and fault diagnosis. Classification algorithms can categorize equipment into different condition states, while regression models can estimate degradation levels or remaining useful life. Algorithms such as Random Forest, Support Vector Machine, Gradient Boosting, Artificial Neural Networks, Long Short-Term Memory networks, and Autoencoders can be used for different types of vehicle-monitoring problems. For bus fleets, however, an important challenge is the heterogeneity of available data. OBD information is primarily numerical and temporal,

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whereas RFID generates event-based identification data. Maintenance records may contain categorical and textual information. Consequently, a multimodal data-fusion approach is required.

Research Methodology. The proposed intelligent assess ment system consists of six major stages:

1. RFID-based vehicle identification;
2. OBD data acquisition;
3. Data preprocessing and synchronization;
4. Feature extraction and data fusion;
5. Machine learning-based condition assessment;
6. Technical condition scoring and maintenance recommendation.

The conceptual architecture can be represented as:

RFID data + OBD data + Maintenance history → Data preprocessing → Feature extraction → Multimodal data fusion → Machine learning model → Technical Condition Index → Bus condition classification → Maintenance decision

This architecture allows information from different sources to be associated with a unique bus identifier.

RFID Data Acquisition. Each bus is assigned a unique RFID identifier. When the vehicle passes an RFID reader, the system records information such as:

- vehicle identification number;
- RFID tag ID;
- date and time;
- location or control point;
- depot entry/exit event;
- maintenance-zone entry;
- inspection event.

The RFID record can be represented as:

$$R_i=(I,D_i,t_i,l_ie_i)$$

where ID_irepresents the bus identifier, $t_i$is the timestamp, $l_i$denotes the location or control point, and $e_i$represents the event type. RFID information therefore provides the contextual layer required for connecting diagnostic observations to individual buses and operational events.

OBD Data Acquisition. The OBD subsystem continuously or periodically collects technical parameters from the bus. A representative parameter vector can be expressed as:

$$O_i(t)=[R,P,M,T_c,V_b,V_s,F_c,DTC_1\ldots DTC_n]$$

where:

$-RPM$— engine rotational speed;
$-T_c$— coolant temperature;
$-V_b$— battery voltage;
$-V_s$— vehicle speed;
$-F_c$— fuel-related parameter;
$-DTC_n$— diagnostic trouble codes.

The selection of parameters should depend on the bus model, engine type, available OBD protocols, and fleet monitoring objectives.

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Data Preprocessing. Raw OBD data may contain missing values, duplicated observations, measurement noise, and abnormal records. Therefore, preprocessing is necessary before model training. The proposed preprocessing procedure includes: removal of duplicate observations, treatment of missing values, detection of outliers, normalization of numerical variables, encoding of categorical variables, synchronization of RFID and OBD timestamps, aggregation of high-frequency measurements.

For a numerical feature x, min-max normalization can be expressed as:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}}$$

This transformation places different parameters on a comparable scale.

Feature Engineering. The effectiveness of the intelligent model depends significantly on the quality of extracted features. Instead of using only instantaneous OBD values, the proposed approach uses statistical and temporal characteristics. Important features include: mean engine temperature, maximum engine temperature, temperature variance, average engine speed, abnormal RPM frequency, battery-voltage deviation, number of diagnostic trouble codes, frequency of repeated diagnostic codes, duration of abnormal operation, fuel-consumption deviation, number of maintenance events, time since the last maintenance operation, number of RFID-recorded depot entries, number of emergency maintenance events.

For a parameter x, the moving average over a time window $w$can be calculated as:

$$MA_t = \frac{1}{w}\sum_{k=0}^{w-1} x_{t-k}$$

The moving average helps identify persistent deviations rather than reacting to isolated measurements.

Multimodal Data Fusion. A key contribution of the proposed model is the integration of RFID and OBD information. RFID data provide the identity and operational context of a vehicle, while OBD data provide technical information. Maintenance records provide additional historical context.

A unified data record may therefore be represented as:

$$X_i = [R_i, O_i, M_i]$$

where $R_i$is the RFID feature vector, $O_i$is the OBD feature vector, and $M_i$represents maintenance-history features. The fusion process can be performed at the feature level. After normalization and encoding, the features are concatenated into a unified representation that is supplied to the machine learning algorithm.

Intelligent Technical Condition Assessment Model. The proposed system divides buses into three technical condition categories:

- Normal condition the vehicle operates within expected technical parameters;
- Warning condition abnormal indicators are present and additional inspection or preventive maintenance is recommended;
- Critical condition significant or persistent abnormalities indicate a high maintenance priority.

A machine learning classifier can be trained to estimate:

$$P(C_k \mid X)$$

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where C_k represents a technical condition class and X represents the integrated feature vector. Random Forest is particularly suitable for an initial implementation because it can handle nonlinear relationships, mixed feature types, and interactions between multiple technical indicators.

The Random Forest prediction can be expressed as:

$$\hat{C}=mode\{h_1'(X),h_2'(X)...h_N(X)\}$$

where $h_j(X)$ represents the prediction of the j-th decision tree.

Technical Condition Index**.** In addition to categorical classification, an interpretable numerical index is proposed.

The Technical Condition Index (TCI) can be formulated as:

$$TCI=100-\sum_{j=1}^{m} w_j D_j$$

where:

−TCI— Technical Condition Index;

−D_j— normalized deviation or risk score of parameter j;

−w_j— importance weight of parameter j;

−m— number of evaluated parameters.

The weights satisfy:

$$\sum_{j=1}^{m} w_j =1$$

A higher TCI indicates a better technical condition.

An illustrative classification scheme may be defined as follows:

TCI Range	Condition	Recommended Action
80–100	Normal	Continue operation and routine monitoring
60–79	Warning	Conduct preventive inspection
0–59	Critical	Prioritize detailed diagnostics and maintenance

These thresholds should not be considered universal. They should be calibrated using historical fleet data, expert assessments, failure records, and operational requirements.

Risk Score. The model can also calculate a failure-risk score:

$$Risk=1-P(C_{Normal} \mid X)$$

A high risk value indicates that the current data contain characteristics associated with abnormal technical conditions. This approach enables fleet managers to prioritize vehicles for inspection without waiting for a complete failure.

Results and Discussion. The integration of RFID and OBD data is expected to improve the reliability of bus condition assessment compared with systems that rely exclusively on either source. An OBD-only model can detect technical abnormalities but may face difficulties in associating observations with maintenance events or operational locations. RFID provides the identity and event context necessary to connect technical measurements with a particular bus and its maintenance history.

The proposed system therefore creates a continuous digital chain:

Vehicle identification → operational event → diagnostic data → condition assessment → maintenance decision.

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This chain can improve traceability and reduce the fragmentation of fleet information.

Comparative Assessment of Data Sources

Data Source	Main Information	Advantages	Limitations
RFID	Vehicle identity and operational events	Automatic identification and event tracking	Does not directly measure technical condition
OBD	Engine and electronic parameters	Real-time technical information	Parameter availability varies by vehicle
Maintenance records	Repair and service history	Provides historical context	Often manually recorded
Integrated model	Combined technical and contextual information	Comprehensive condition assessment	Requires data integration infrastructure

The table demonstrates that no single data source is sufficient for comprehensive assessment. The proposed model addresses this limitation through multimodal data fusion.

Predictive Maintenance Potential. The proposed model can transform traditional preventive maintenance into a more condition-based approach. Instead of performing maintenance exclusively according to fixed intervals, maintenance priorities can be determined according to the estimated condition of each bus. For example, a bus may have moderate mileage but exhibit repeated high-temperature events and recurring diagnostic codes. Under a conventional mileage-based strategy, the vehicle might not yet be scheduled for maintenance. Under the proposed intelligent system, the vehicle would receive a higher maintenance priority because the combined evidence indicates an elevated technical risk. Similarly, a bus with high mileage but stable diagnostic parameters and no significant recurring faults may remain in routine monitoring.

Role of Historical Data. Historical maintenance information is particularly important for improving model reliability. Repeated diagnostic codes, repair frequency, component replacement history, and time since the last service can reveal degradation patterns.

A temporal degradation indicator can be expressed as:

$$D_t=\alpha D_{t-1}+(1-\alpha)E_t$$

where D_t represents the current degradation estimate, E_t is the current abnormality score, and α controls the influence of historical observations. This formulation enables the model to distinguish between temporary anomalies and persistent degradation.

Practical Application in Urban Bus Fleets. The proposed framework can be deployed in a centralized fleet-management platform. RFID readers can be installed at depots, maintenance stations, and inspection points. OBD devices can transmit diagnostic data to a central server using available wireless communication technologies.

A fleet-management dashboard can display: current TCI for each bus, buses requiring inspection, recurring diagnostic trouble codes, abnormal parameter trends, maintenance history, high-risk vehicles, fleet-wide technical condition statistics. Such a dashboard can help maintenance managers allocate limited resources according to objectively measured technical indicators.

Model Validation Strategy**.** To validate the proposed model, a real-world dataset should be collected from a representative bus fleet over a sufficiently long observation period. The dataset should include: RFID event records, OBD measurements, diagnostic trouble codes, maintenance records, mileage, operating hours, environmental conditions where available, confirmed failures and component replacements. The dataset should be divided into training, validation, and testing subsets.

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The model can be evaluated using:

$$Accuracy=\frac{TP+TN}{TP+TN+FP+FN}$$

For multiclass classification, precision, recall, F1-score, and confusion matrices should also be considered.

For imbalanced datasets, macro-averaged F1-score is particularly useful because it prevents the performance metric from being dominated by the most common class.

A baseline comparison should be conducted between:

1. OBD-only model;
2. RFID + OBD model;
3. RFID + OBD + maintenance-history model.

This experimental design would allow the contribution of multimodal data integration to be quantitatively evaluated.

The proposed model demonstrates a conceptual pathway toward intelligent bus-fleet maintenance. Its primary advantage is the integration of identification, diagnostic, and historical information into a unified analytical framework. However, several challenges must be considered. First, OBD parameter availability differs among bus manufacturers and vehicle generations. Second, RFID infrastructure requires appropriate reader placement and reliable communication. Third, machine learning performance depends strongly on the availability and quality of historical failure data. Another important issue is model interpretability. Fleet maintenance personnel may be reluctant to rely on a prediction without understanding the factors contributing to the assessment. Therefore, the proposed system should provide explainable outputs, such as: “high coolant-temperature deviation”, “repeated diagnostic trouble code”, “increased abnormal-event frequency”, “long maintenance interval.” Explainable machine learning can increase user confidence and facilitate practical maintenance decisions. Data security is also important because connected fleet systems collect operational information continuously. Appropriate authentication, access control, encryption, and secure communication mechanisms should therefore be incorporated into the system architecture.

Conclusion. This study proposed an intelligent model for assessing the technical condition of buses based on the integration of RFID and On-Board Diagnostics data. RFID technology provides reliable vehicle identification and operational-event information, while OBD systems provide detailed technical indicators and diagnostic information. Combining these data sources creates a more comprehensive representation of vehicle condition than relying on a single information source. The proposed framework includes data acquisition, preprocessing, feature engineering, multimodal data fusion, machine learning classification, and calculation of a Technical Condition Index. The resulting system can categorize buses into normal, warning, and critical conditions and can support maintenance prioritization. The model has the potential to improve fleet availability, reduce unexpected failures, strengthen maintenance traceability, and support the transition from traditional scheduled maintenance toward condition-based and predictive maintenance. Future research should focus on collecting large-scale real-world bus-fleet datasets and experimentally comparing Random Forest, Gradient Boosting, Support Vector Machine, LSTM, Autoencoder, and hybrid machine learning models. Further research should also investigate remaining useful life prediction, explainable artificial intelligence, edge computing, and real-time deployment in intelligent transportation systems.

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