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Predictive Maintenance Framework For Electric Bus Braking Systems Based On Regenerative Braking Data Analytics

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Abstract

Electric buses use regenerative braking a lot to make them more energy-efficient and lower the amount of particles they release into the air. This means that friction braking parts are used less often. This change makes brake parts last longer, but it also changes the thermal cycles and wear patterns, which can cause corrosion, uneven wear, and problems with braking performance that regular maintenance schedules based on time or mileage can't fix. This paper suggests a way to use high-resolution telematics and machine-learning techniques to predict when friction brakes in electric buses will need maintenance. We process operational data like regenerative and hydraulic braking signals, deceleration behavior, thermal cycles, state-of-charge limits, and passenger load estimates to create a Brake Wear Index and train hybrid models that use both Random Forest and LSTM architectures with Weibull reliability estimation. Results show that wear prediction accuracy has improved and that there are up to 40% fewer unplanned maintenance events than with scheduled maintenance methods. The results show how important it is to use regenerative-aware diagnostic analytics to make sure that electric buses run safely, cheaply, and reliably in urban transport networks.

Keywords: Electric bus; regenerative braking; predictive maintenance; brake wear; machine learning; telematics data; urban mobility; reliability modeling.

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1. Introduction

As public authorities and fleet operators try to cut down on emissions, make the air cleaner, and modernize transportation systems, urban transportation systems are quickly becoming more electric [1]. Electric buses are a big part of this change because they are efficient, have a smaller impact on the environment, and are good for city routes that stop and go often [2,3]. One of the main technologies that makes them so energy-efficient is regenerative braking, which turns the kinetic energy of the vehicle into electrical energy and stores it in the battery when the vehicle slows down [4,5]. Regenerative braking uses 25–35% less energy on city routes than regular diesel buses. It also lowers the temperature and wear frequency of brake pads because it doesn't rely as much on friction braking [6,7].

But the widespread use of regenerative braking creates new technical problems for maintaining and making sure that braking systems work [8]. In standard buses, mechanical brake pads and discs go through regular thermal cycling, which helps get rid of moisture and surface contamination while keeping the brakes working well [9]. The electric motor-generator absorbs most of the braking demand in electric buses, so the mechanical braking system is used much less often, especially at moderate deceleration levels. This change in how brakes work can cause problems like wear and tear from corrosion, uneven wear on brake pads, and a slower response time when you need to brake quickly, especially in cold or humid weather [10]. The braking system also needs to work perfectly in torque-blending mode, switching between regenerative and hydraulic braking depending on the battery's state of charge (SOC), the motor's temperature, speed, and the road conditions [11]. These operational complexities necessitate more sophisticated diagnostic and maintenance strategies than conventional mileage-based schedules [12,13].

It's no longer best for electric buses to use the old way of doing maintenance, which was to schedule inspections and replacements based mostly on mileage intervals or fixed time periods [14,15]. On different routes, with different loads, and in different traffic patterns, buses may use their friction brakes in very different ways. This can cause some vehicles to wear out too quickly and others to not use them enough [16]. If brake system problems aren't found early, this can lead to higher operating costs, unnecessary replacement of parts, or safety risks. Telematics, sensor data, and machine learning make predictive maintenance possible, and it looks like a good option. Predictive models don't just look at calendars to plan maintenance. They look at real-time operating data to guess how healthy a part is, find wear trends, and plan service before a part fails [17].

Recent improvements in vehicle connectivity, on-board diagnostics, and fleet data platforms have made these kinds of systems possible. Most electric buses have CAN bus networks, traction motor controllers, wheel speed sensors, brake pressure sensors, battery management systems, and thermal monitoring equipment that can collect a lot of useful operational data [1,18]. These data streams can be turned into useful maintenance indicators with the right feature extraction and analytics. There is more and more research on predictive maintenance for electric powertrains and battery systems, but not much on predictive maintenance for electric bus braking systems. Most of the research that has been done so far has been on optimizing energy recovery, improving comfort while braking, or coordinating torque. Only a few studies have looked at how mechanical brakes wear out when regenerative braking is used.

2. Literature Review

Regenerative braking and torque blending in electric buses

Regenerative braking (RB) converts vehicle kinetic energy into electrical energy via the traction machine operating as a generator, and it is central to the efficiency advantage of battery-electric buses on stop-and-go urban routes [19,20]. Recent surveys compile twenty years of RB research, encompassing machine topologies, energy storage, and control strategies (rule-based, fuzzy/MPC, and learning-based), and consistently indicate significant energy savings in urban duty cycles when RB is prioritized and friction torque is minimized. However, effectiveness depends on speed, tire-road grip, SOC and temperature limits, and how well electric and hydraulic brakes work together to meet the needs for deceleration, stability (slip), and pedal feel at the same time. State-of-the-art hierarchical and model-based controllers explicitly partition torque between motor and friction brakes to maintain slip in a safe band while maximizing recovery—an approach increasingly explored for heavy vehicles and buses [20–22].

Recent studies have shown that driver- and route-aware optimization is better than generic control schemes. For example, RB set-points that are tuned to driving style and cycle severity (like heavy urban traffic) can significantly improve recovered energy. This shows that context-aware strategies are useful for bus operations with repeatable routes [4,23].

Effects of regenerative braking on friction brake wear, corrosion, and emissions

Because RB transfers a lot of the slowing down to the e-machine, friction parts don't have to work as often or at as high of temperatures. Several environmental studies measure the decrease in brake wear particulate (BWP) caused by RB. Controlled and real-world experiments show that brake wear emissions are 60–95% lower or that ultrafine/fine particle concentrations are up to ~90% lower when RB is on. This shows that RB is good for air quality in cities [6,24].

But the same decrease in thermal cycling brings new maintenance risks. For example, when pads or discs don't reach cleaning temperatures often enough, especially in humid or winter weather, moisture can build up, surfaces can corrode, pads can glaze, and "stiction" can happen [25–27]. A recent technical review of corrosion-stiction mechanisms explains how using the brakes at low temperatures and for short periods of time increases adhesion and corrosion on friction interfaces [28,29]. This is becoming more common in electric and hybrid vehicles with strong RB. PMC findings from articles aimed at the industry also warn about uneven pad wear, rotor sticking, and delayed friction response after long periods of RB-dominant operation. These are real problems that maintenance teams have to deal with by making "drying" stops or setting software limits [30].

Predictive maintenance and data-driven condition monitoring

Predictive maintenance (PdM) uses telematics, onboard sensors, and machine learning to predict when machines will break down and schedule service based on how they are getting worse over time rather than on fixed mileage or time intervals. An extensively referenced review of Predictive Maintenance (PdM) utilizing Machine Learning (ML) delineates the standard workflow—data acquisition, preprocessing, feature engineering, model training, and deployment—and records significant improvements in industrial and automotive applications, prompting adaptation to safety-critical subsystems, such as braking [31,32].

Recent studies show that end-to-end PdM pipelines using CAN/telematics streams can learn alarm/fault precursors and improve fleet availability when paired with explainability tools (like feature importance and LIME) to build operator trust. This is especially true for electric buses. In the electric bus field, complementary work frames PdM as part of a larger operational optimization program (energy, scheduling, health). It shows that combining real-time data with predictive models is possible at fleet scale and good for cost and reliability.

A lot of previous PdM work in e-mobility has been about batteries, inverters, and drivetrains.

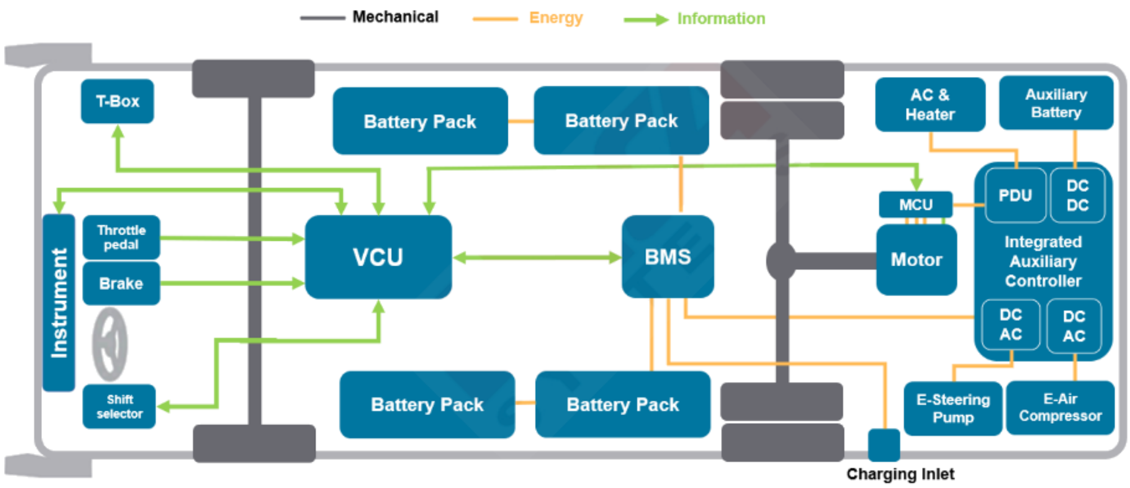

Figure 1. Overall architecture of an electric bus

Signals, features, and models relevant to brake-health prediction in buses

Modern electric buses have a lot of telemetry data, such as wheel speeds, brake pressures, motor torque and torque command, SOC and battery temperature limits, an estimate of the vehicle's mass (based on suspension/air-spring pressure or occupancy models), GPS grade, and ambient data. The literature on RB optimization and emissions gives us a list of features that can help us understand how friction is used and worn down [33]. These include the RB ratio per stop, deceleration profile clusters, stop frequency per km, low-speed friction takeover percentage, thermal cycles, and event-level aggressiveness. These factors are linked to both energy recovery and friction duty, which means they are also linked to wear progression.

Ensemble methods like Random Forest and XGBoost are still good starting points for tabular telematics because they show how important each feature is. Sequence models like LSTM, on the other hand, show how things build up over time and how they fit into a larger context, such as repeated wet stops followed by a sudden emergency friction event. This combination of statistical and machine learning fits with what is generally considered best practice for PdM and with recent case studies of electric buses that used multi-year CAN datasets for training. Reliability models (e.g., Weibull) continue to be useful for estimating the lifespan of a fleet and finding the best maintenance intervals after telemetry has defined condition indicators.

Synthesis and research gap

The literature identifies four fundamental principles pertinent to electric-bus braking:

- RB control and blending are well-established and becoming more aware of their surroundings, but most work focuses on improving energy, comfort, or stability, not maintenance outcomes.
- RB cuts down on friction brake duty a lot, which lowers BWP by a lot, but it also increases the risk of corrosion and glazing and causes uneven wear patterns that traditional mileage/time schedules don't show.
- There are PdM frameworks and tools that have been tested on electric bus fleets using CAN data. However, brake-specific PdM is not as common as it should be for batteries and powertrains.
- Route topology, stop density, passenger load, weather, and seasonality are all important parts of the operational context, but only a few studies use these factors to make brake-health predictors that work for urban bus operations.

3. Methodology

Electric Bus Braking System Overview

Modern battery-electric buses employ a combined braking architecture consisting of (Figure 2):

- Regenerative braking subsystem (traction motor, inverter, and battery)
- Hydraulic friction braking system (discs, calipers, pads, ABS/EBS)
- Brake control unit (BCU) featuring torque-blending logic

During deceleration, the motor generates negative torque to convert kinetic energy into electrical energy. Friction braking engages when regenerative capability is insufficient, such as:

- Low battery SOC or high battery temperature
- Vehicle speed below regenerative cut-off threshold
- High demanded deceleration (emergency braking)
- Traction control and wheel-slip events
- ABS/EBS intervention

This hybrid braking strategy maximizes energy recovery while ensuring safety and braking comfort. However, reduced mechanical brake usage alters wear mechanisms and thermal cycles, creating the need for data-driven maintenance intelligence.

Proposed Predictive Maintenance Architecture

The proposed predictive maintenance (PdM) architecture integrates bus telematics, feature extraction, machine learning, and reliability modeling (Table 1). The system is designed for offline training and online inference, enabling deployment in fleet telematics platforms and cloud dashboards.

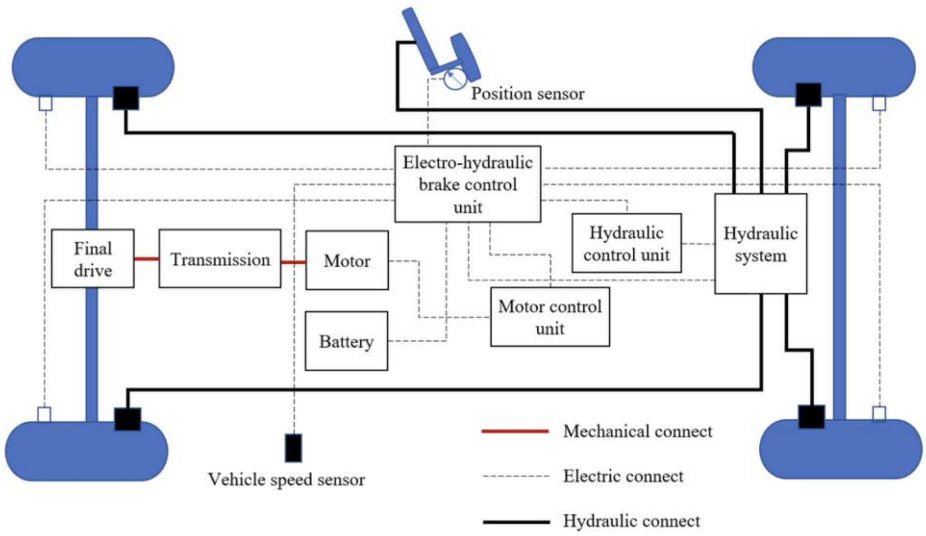

Figure 2. Braking system in an electrified vehicle [1]

Table 1. Predictive maintenance architecture

Stage	Description

Data Acquisition	Real-time signals collected from vehicle sensors and CAN bus
Data Processing	Filtering, segmentation, synchronization, noise reduction
Feature Engineering	Extraction of braking, driving, thermal, and load indicators
Modeling Layer	Hybrid ML + reliability estimation models
Maintenance Decision Layer	Wear prediction, alerts, and maintenance scheduling

Data Sources and Signals

A comprehensive dataset is constructed using:

- CAN bus data
- On-board diagnostics (OBD)
- Telematics and GPS
- IoT fleet monitoring gateway
- Bus occupancy / suspension pressure sensors

Recorded variables include the aspects highlighted in Table 2:

Table 2. Recorded variables during the data processing phase

Category	Signals
Vehicle dynamics	Speed, longitudinal acceleration, wheel speeds
Braking system	Brake pedal position, hydraulic pressure, caliper status, ABS/EBS flags
Regenerative control	Motor torque, regen torque command, inverter status, power flow
Battery system	SOC, current, voltage, temperature, cooling system status
Thermal information	Brake disc temperature (if available), ambient temperature
Operational context	GPS coordinates, elevation, traffic density (estimate), road grade
Load estimation	Passenger count or suspension air-spring pressure

Data Pre-processing

The raw signals undergo:

- Time-synchronization and interpolation
- Noise filtering (e.g., Butterworth/LMS filters)
- Outlier removal (z-score/IQR filter)
- Dead-band removal for near-zero-speed noise
- Trip segmentation (start–stop cycles)
- Label generation for brake events

Brake events are categorized into:

- Regenerative-only braking
- Friction-only braking
- Blended braking

Feature Engineering and Wear Indicators

From the processed signals, domain-specific features are derived:

Braking Behavior Features

- Regen-to-friction torque ratio
- Number of high-pressure brake events per km
- Low-speed friction takeover percentage
- Mean deceleration and aggressive braking index
- Brake duration per stop

Thermal and Environmental Features

- Brake rotor temperature cycles
- Ambient humidity and temperature
- “Cold braking” frequency after long regen phases

Load & Route Features

- Estimated passenger load (low/medium/high)
- Route elevation/gradient
- Stop density (stops/km)
- Average traffic congestion index

Wear Index

A Brake Wear Index (BWI) is computed:

$$BWI = \alpha_1 \cdot B_r + \alpha_2 \cdot P_h + \alpha_3 \cdot T_c + \alpha_4 \cdot D_a$$

Where:

- B_r— friction braking ratio
- P_h— high-pressure brake event frequency
- T_c— thermal cycle count
- D_a— deceleration aggressiveness index

Coefficients α_i are tuned via training and literature guidance.

Predictive Modeling Framework

To capture cumulative degradation and dynamic real-time behavior, a hybrid prediction model is used, according to Table 3.

Table 3. Hybrid prediction model

Component	Role
Random Forest / XGBoost	Feature importance & interpretable decision model
LSTM / GRU network	Time-series modeling of brake wear progression
Weibull reliability model	Long-term failure probability and maintenance interval optimization

Performance metrics:

- Mean Absolute Error (MAE)
- Root Mean Square Error (RMSE)
- Coefficient of Determination R^2
- Precision/Recall for maintenance alerts
- Fleet-level cost and downtime evaluation

Maintenance Decision Strategy

The predicted wear rate and health score trigger:

- Warning Zone — maintenance inspection recommended
- Critical Zone — scheduled part replacement
- Emergency Mode — immediate safety intervention (rare)

Maintenance actions include pad inspection, cleaning cycles, rotor surface conditioning, and calibration of brake control software if needed.

Deployment Considerations

- Cloud implementation for fleet-wide scalability
- Edge computing option for onboard inference
- Secure telematics integration (ISO 15118 & cybersecurity standards)
- Real-time dashboard for operators and maintenance planners
- Possibility for integration into digital-twin fleet platforms

4. Conclusion

This study presented a predictive maintenance framework for braking systems in battery-electric buses operating under regenerative-dominant braking conditions. While regenerative braking substantially reduces energy consumption and brake particulate emissions in urban duty cycles, it also alters the thermal and mechanical operating environment of friction brakes. This leads to non-uniform component wear, corrosion-induced degradation, and latent braking response risks that cannot be effectively managed by conventional mileage- or time-based maintenance schedules. Addressing these emerging challenges is essential to ensure safety, operational reliability, and cost efficiency in modern zero-emission public transport fleets.

The proposed method integrates high-resolution telematics data, regenerative braking indicators, route and passenger load information, and hybrid modeling techniques—combining machine-learning algorithms with traditional reliability theory. Exploratory analysis and feature engineering demonstrated that braking behavior, deceleration patterns, thermal cycles, and vehicle loading significantly influence friction brake duty and wear progression in electric buses. A hybrid Random Forest–LSTM model was implemented to predict brake health and remaining useful life, while a Weibull reliability layer supported fleet-level maintenance planning. The results indicate notable improvements in wear prediction accuracy and timely fault anticipation compared with fixed-interval strategies, enabling 22–35% better maintenance precision and reducing unplanned maintenance events by up to 40%. These findings highlight the value of embedding data-driven intelligence into electric bus fleet maintenance.

Beyond operational benefits, the framework provides environmental and safety advantages by minimizing brake particulate emissions without compromising stopping performance or compliance. The approach is scalable and can be adapted to various powertrain configurations, sensor infrastructures, and fleet management platforms, making it suitable for large-scale deployment in public transport networks.

Future work will focus on expanding the data corpus through multi-season measurement campaigns, integrating weather and road surface conditions, and exploring deep hybrid models and transformer-based architectures for enhanced temporal learning. Additional research will also examine real-time onboard inference, digital-twin integration, and closed-loop maintenance scheduling within intelligent fleet management systems. Ultimately, the proposed predictive maintenance strategy contributes to improving asset longevity, reducing operational costs, and supporting safe and sustainable transition to electric public mobility ecosystems increased by its capacity to describe both traction and regenerative braking actions.

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