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Enhancing School Bus Engine Performance: Predictive Maintenance and Analytics for Sustainable Fleet Operations

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Abstract

A smart solution for preventive information, diagnostics, and prognostics for durable engine management on school buses will improve vehicle safety and performance, reduce maintenance costs and time, and extend vehicle life while minimizing environmental impacts. Additionally, the solution provides knowledge to the school district on effective vehicle maintenance; it enhances students' welfare and educational outcomes. School transportation is the only major public transit system for children, which operates two trips a day each school day. 480,000 yellow school buses transport 25 million children 3.3 million miles to and from school. Researchers have shown exacerbated environmental and health impacts from considerable emissions and idle time. Schools are increasingly choosing diesel engine vehicles over hybrid or electric power vehicles. The higher acquisition and maintenance costs, the reliance on battery power based on outside temperature, and the requirements of off-route and after-school activities have limited the investment in these alternative power school buses. The interest in this paper is primarily based on diesel-powered school buses that constitute 90% of school buses and trips. High emission durations caused by aging and/or poor maintenance of school buses are a result of the non-usage of technologies and management practices to achieve low emissions. Its growth is hindered by the inability of some school districts to detect engine damage early, poor excuses regarding the price for effective maintenance, and uncertainty about maintenance cost savings and equipment longevity.

The proposed diagnostic and prognostic maintenance solution employs an open-source machine learning algorithm to train bus engine and emission rate models and minimize idle time and wear parts using vehicles' sub-minute real-time GPS locations, vehicle-activated event logs, and real-time diagnostics. The training database manages a variety of engine models by replacing training data with diagnostic and prognostic information in a model training feedback loop with engine manufacturers. The environmental algorithm for real-time emissions rate measures the most discriminant temperature, pressure, and emissions for idle time and proposed torque sub-ranges. The algorithms are portable to passenger buses, fire trucks, police vehicles, snow plows, street sweepers, traffic management vehicles, and construction vehicles that often perform daily short, low-speed, and stop-and-go cycles and are driven by student drivers. Pilot implementations performed for school buses in Los Angeles have shown promising results. The full proposed solution can be implemented using existing resources in the transportation community.

Keywords: Predictive Maintenance,Engine Performance,Fleet Management,School Bus Optimization,Data Analytics,Sustainability,Performance Monitoring,Operational Efficiency,Maintenance Scheduling,Condition-Based Maintenance,Fuel Efficiency,IoT in Transportation,Predictive Analytics,Cost Reduction,Emission Control,Reliability Engineering,Asset Management,Safety Compliance,Real-time Monitoring,Transportation Sustainability.

1. Introduction

School bus transportation is the safest form of student transportation and is crucial for the functioning of an educational system. The United States has one of the largest school bus fleets in the world, with approximately 500,000 school buses operating every day and covering around 3.6 billion miles annually. As most buses are equipped with diesel engines, the fleet is responsible for substantial carbon emissions, and the health and environmental concerns associated with diesel vehicles have sparked interest in alternative strategies and technologies. Until a transition to technologically advanced options is completed, ensuring that the existing school bus fleet is managed in the most efficient way and with the least environmental impact is vital. However, effective transportation management in the context of school bus operations is a complex issue that involves multiple heterogeneous aspects and has to be solved under considerable operational constraints, including those about cost, time, policy, and operations.

To address these issues, it is necessary to develop methods and technology to help school bus fleet managers in their decision-making processes. One such method is predictive maintenance because school buses are predominantly powered by internal combustion diesel engines, and they usually serve sparse and repetitive routes between home and school, which results in poor engine performance and degradation of student health and the quality of education. Predictive maintenance is a well-known concept in transportation, and there has been considerable research and numerous publications on the topic. The analytics and engineering behind predictive maintenance are in aviation's DNA, where increasing availability to today's tightly scheduled fleets without compromising safety standards was the primary goal at the birth of this concept. The situation is similar in the trucking industry, where predictive maintenance can also assist logistics and leasing companies, and vehicle manufacturers in improving their service, reliability, and safety, and assist them in gaining a competitive edge.

Fig 1: Fuel Monitoring for School Bus

1.1. Background and Rationale

School buses are the safest mode of pupil transportation in terms of injuries and fatalities and represent the most common form of pupil transport. Their role is especially crucial in the United States, where more than 25 million students routinely use buses for transportation to and from school. For 55% of these students, this form of transportation is the only means to access education. As such, school bus service is essential in many ways for local communities, families, and children.

The benefits of school bussing need to be balanced against the environmental and financial costs concerning school bus operations. Buses emit substantial amounts of pollutants that contribute to air quality issues such as ground-level ozone formation, particulate matter, and related health issues. Diesel particulate matter has been shown to contribute to lung-related illnesses and asthma. Children are at a greater risk of developing pollution-related lung diseases than adults. Diesel exposure is linked to adverse health risks, and children's exposure levels are significantly elevated when they are riding in buses. Diesel exhaust is classified as a likely human carcinogen, and evidence from lung carcinogenesis shows an association with bus riding for certain populations. Finally, school district operating budgets bear the costs associated with school bus operations.

1.2. Research Objectives

The primary objective of the study was to harness the power of predictive analytics and bring to fruition a comprehensive supervisory system employing a novel real-time decision framework for enhanced engine performance in school buses. Specific objectives of this research are categorized as follows: 1. To identify and implement advanced monitoring functions that capture dynamic real-world behavior of the school bus engine through data mining and feature extraction of high-dimensional telematics data. 2. To develop and deploy state-of-the-art big-data-ready machine learning models for providing advanced warning of impending performance degradation, inefficiencies, or defects in the engine of a current model year school bus. 3. To build a real-time predictive maintenance system for first responders and maintenance support staff that provides timely, individually tailored information regarding further inspection, component testing, or immediate or near-term operational requirements before the occurrence of serious degradations or failures while the buses are in service. 4. To deliver robust construction, retrofit, and maintenance recommendations for transportation managers to ensure efficient, reliable, and sustainable school bus operation that incorporates advanced vehicles and autonomy developments designed to provide energy conservation, reduced emissions, and optimal engine performance. 5. To compare fitness for intended purpose criteria between baseline and improved vehicles and measure potential savings.

Equ 1: Mean time between failures

$$\mathrm{MTBF} = \frac{\sum(\text{start of downtime} - \text{start of uptime})}{\text{number of failures}}.$$

In a similar manner, mean down time (MDT) can be defined as

$$\mathrm{MDT} = \frac{\sum(\text{start of uptime} - \text{start of downtime})}{\text{number of failures}}.$$

2. Literature Review

The overall reliability of the planned fleet service is highly dependent on the reliability of school buses. With the move towards vehicle health data analytics, the majority of vehicle reliability efforts are focused on component repair prediction and the scheduling of maintenance through analysis of sensor data, telematics, vehicle trips, and diagnostic trouble codes, although an understanding of the fleet as a whole is notably absent. While Automated Fleet Maintenance has played an important role, recent advancements in technologies related to vehicle health data analytics now allow organizations to take greater advantage of by-product data that has already been captured or obtained from source systems across the fleet. Investing in and taking advantage of these technologies can be categorized as enhancements, undercutting one of the key drivers of Automated Fleet Maintenance. This effort seeks to provide valuable insights for fleet owners by summarizing the distinctive data necessary for proactive as opposed to reactive vehicle maintenance.

Additionally, this paper provides a general step-by-step process to facilitate predictive quality in the absence of all necessary component repair prediction study data, thereby eliminating some of the risks associated with this type of fleet enhancement effort. Despite the unique challenge presented by each fleet's individual data sets, a proactive approach to vehicle health data analytics is the hallmark of the improved bills of material, and results can apply to a wide range of vehicle types and fleet sizes. This effort is especially timely given the prevalent use of smartphones by school bus drivers to check all vehicle components at both the beginning and the end of the driver's service. These manual checks suggest maintenance actions that reduce the risk of removing a bus from service between service intervals. An effective data collection framework can be used to incorporate these valuable insights in a data-driven approach that provides greater uniformity across the customer's governance model perspectives.

2.1. Current Challenges in School Bus Fleet Management

In current practice, school bus fleet administrators and operators face many challenges in planning and management to maintain the vehicles. The lack of reliability in school bus services may affect faculty who rely on these services and require consideration from administrative staff in making appropriate changes for the next fiscal year. This may also result in a decrease in operating efficiency and possibly increase the cost of the bus fleet. First, there is no current predictive model in school bus engine maintenance to engage in using the most effective operations with sufficient road life over the entire service life of a school bus because existing operations are performed without any predictive maintenance history to plan and use optimal preventive maintenance approaches. They are not optimized or planned to reduce costs due to the risks associated with unscheduled engine maintenance outcomes.

Second, since there are several participants in engine operation and maintenance activities, including multiple roles in an operator's organization, the focus of a few individuals may lead to issues with fuel, normal storage, draining, and replacing engines without a supported set of procedures. The operator and ideas such as total productive maintenance need to address this dilemma and excuse the operator during its organizational maintenance benchmarking projects. However, there are distributed maintenance benefits that track engine components and collaborate over the supply schedule, including delays in replacing obsolete performance components for long-term service life strategies. Third, challenges also stem from how much unnecessary investment is made, as some important tasks, like relieving specific vehicle overhaul costs and maintaining other products, require ensuring the reliability of engine maintenance operations and effectively utilizing existing maintenance resources.

In school bus fleet management, this is particularly challenging for school buses, as each bus typically carries a set of components that change, affecting how and when the fiscal budget will be impacted due to equipment obsolescence and increased fleet costs. Additionally, obsolescence of the related products reverses the life cycle of the equipment, and configuration changes in the available trained population of maintenance operations, such as collaboration schedules, are not supported for components or equipment in any individual's regular maintenance job. The primary difficulty in designing and implementing a sustainable predictive school bus engine maintenance model is transitioning effectively from our current maintenance-driven operation level to an operation level with increasing accuracy and strength over time. The ignorance or disbelief in this concept by individuals within the motor coach company has been a chief deterrent in developing a much-needed solution. Conducting this development while maintaining operations in most instances without the support of such information is highly challenging for a company.

Fig 2 : Challenges Faced by Fleet Managers in the Logistics Industry

2.2. Predictive Maintenance in the Automotive Industry

During the last few years, predominantly due to the advancement of machine learning models, predictive maintenance has begun to attract the attention of the automotive industry. Real-time monitoring, high prediction accuracy, and the capability of serving the requirements of future automobiles further drive automotive companies to find new algorithms that provide benefits like high accuracy and no lag time. These drive such trends as usage-based insurance, which is based on a policyholder's driving behavior, and no lag predictive failure algorithms to detect a problem and repair it before it leads to a breakdown situation. These types of insurance policies are calculated by certain parameters, including the duration and distance the vehicle is driven, time of driving, speed, braking, acceleration, and location. However, the derived statistical data may not be adequate to efficiently predict the potential loss of using this data since such real-time and big data load evaluation issues are very demanding in embedded systems when considered for in-vehicle usage.

New trends also aim for the development of models capable of tracking predictors and parameters related to the state of the vehicles, including their degradation and lifetime estimation. The developed algorithms are produced using two-dimensional heatmap data; this data is obtained from the recorded random degree profiles during vehicle launch for a certain time. This is just one example that illustrates the direction of the work in the automotive area, such as the widely used oversampling techniques and synthetic data generation algorithms that are using deep learning models to classify the remaining useful life of a bearing. Other works categorize recent publications dealing with health monitoring and predictive maintenance, including the application of the Internet of Things for predictive maintenance and the use of deep learning tools for implementing fault classification of automotive engines.

2.3. Analytics and Data-Driven Decision-Making

Several data apps already exist to collect and analyze the behavioral patterns of transportation passengers. However, now with affordable small-size sensors that can communicate through IoT, new data analytics and behavior pattern prediction become possible, benefiting both transportation administration, social scientists, and passengers. Data analytics and predictions that forecast if the Monday morning rush hour extra infrastructure is needed could be very useful for controlling budgets. An interesting data platform to explore would be an accurate student headcount every minute for all the bus stops on the route. The accurate headcount data on student drop-offs can be interesting for truancy officers. How many students were late or missed their ride is also interesting data that can be analyzed to help set up better scheduling strategies for these students.

However, an interesting data analysis platform to explore is related to questions like what the peak times were. What are the loading times for students over a typical exposure time, or the area under the curve for the dwell times? How much time did our students spend at a given location? Business data analysis and daily, weekly, monthly, or end-of-year comparisons can also provide ample opportunity for service optimization. Very interesting will be the exploration of the serviceability of the proposed data system to use it as the "bus headcount book." For decades, transportation student data collection has been using the recording of a bus headcount every time the bus arrives or leaves a physical point or student bus stop as a very useful traditional method.

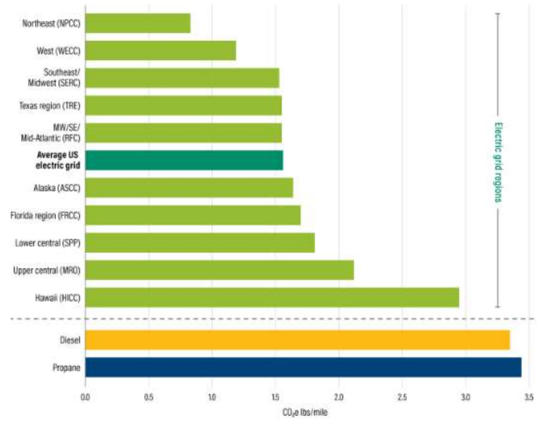

Fig : Electric School Buses are the Best Choice to Reduce Emissions

3. Methodology

With the advancement in digital technologies and connectivity, it's the right time for fleet operators to optimize traditional approaches, such as preventive maintenance, and utilize more rigorously the predictive maintenance possibilities offered by these technologies. This study proposed a data-driven maintenance methodology of predictive analytics using a model for temporary load-sheds and preventive engine maintenance strategies. The deployed direct-replacement and structured time scale datasets were trained and independently tested for accuracy, properly projected responsiveness, and the best practices of maintenance scheduling and tasks. The pilot study resulted in better than 90% truck travel time average savings with clogged filter and non-clogged filter forecasts in the existence of replacement supplies, and the investments in these supplies would be profitable considering the savings or penalty cost for not reaching drop-off and pick-up timetables. Comparatively, the study successfully illustrated the saving efficiency potential of the model in actually deploying other preventive treatments of pinging and ridiculed fuel conditions. The structural timescale is designed flexibly enough to monitor not only scheduled checks but also load-dependent sensitivity and complex stochasticity. The proposed structured timescale technique approach is scalable due to its plug-in evaluation nature and is attractive to operators with various levels of computing expertise.
Our contribution distinguishes itself from the long list of vehicle history datasets of severe driving conditions, which offered a considerable number of external and complex control signal evaluations with clogged conditions. The prior maintenance method research has much smaller datasets and does not measure the actual financial efficiency of the proposed predictive treatments. Our direct-replacement dataset represents not the competitive aspiration of the predictive messages that could be received by the driver, but the actual technical availability of refill inventory. The wide versatility of using these datasets on other distribution centers offers the possibility of even shorter testing periods of the entire predictive technique in practice. Studies have evaluated the available prognostics benchmark datasets, but they usually have been limited to the forecasting alerts of either unscheduled bus line changes or downloads. More importantly, these benchmark dataset tests lack the crucial classification methods of different temporary treatments, clogged and sufficient conditions, through our deployed sophistication of the model.

Equ 2: Queues Customers arrive according to a Poisson process with rate

$$\rho = \frac{\lambda}{\mu} \qquad W = \frac{1}{\mu - \lambda}$$

$$\pi_0 = P(N=0) = (1-\rho) \qquad L = \lambda W = \frac{\lambda}{\mu - \lambda}$$

$$\pi_n = P(N=n) = \rho^n (1-\rho) \qquad W_q = W - \frac{1}{\mu} = \frac{\lambda}{\mu(\mu - \lambda)}$$

$$L_q = \lambda W_q = \frac{\lambda^2}{\mu(\mu - \lambda)}$$

3.1. Data Collection and Sources

This study used a dataset that includes more than 14,000 bus trips during the 2015–2016 and 2016–2017 school years. The

dataset documents buses' GPS records for approximately one school year and contains two types of GPS data: a daily data file detailing buses' geographical coordinates every 60 seconds and a unique established list of stops encountered. Additional features in this GPS dataset related to bus type, VIN, and engine family brand make the data more informative. The fleet management data file, which corresponds to the GPS dataset, informs this study of bus maintenance history. The dataset was descriptively explored to understand its characteristics. Due to non-progressiveness, the recorded speed of less than 1 mile per hour was analyzed. During the period under review, the fitted bimodal mix model identified a cohort-based reporting pattern: there is a high/low-speed separation around 7:30/14:00, which on examination coincides with the school's starting and ending times.
The dataset was cleaned and consolidated to fit the predictive modeling. Data cleaning began with removing GPS data with problematic quality before additional features were derived. Geographic features were derived; one of these features was the slope. Other features were derived as wear-and-tear indicators, including cumulative stop numbers, temporal countdown features, six aggregate summary statistics such as cumulative speed fluid movements, and time series indices. A trips-based dataset is one data file for every trip taken by all available buses. Helper parameters were obtained, which used school front door and stop, door/bay/route programs, operation/transportation service providers, insurance group schemes, black strokes, and energy audits. For this descriptive analysis, school bus system characteristics were also used in terms of use and usage, as well as infrastructure requirements for a predictive task.

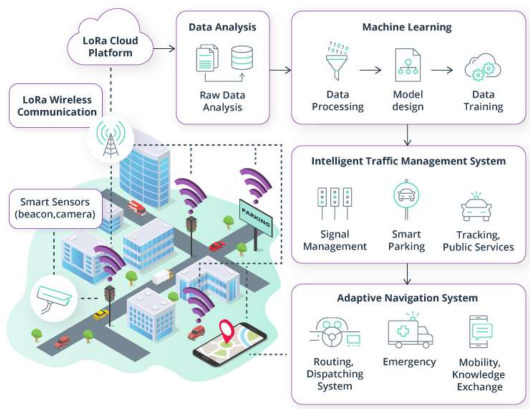

Fig 3: Data Analytics in Transportation Planning

3.2. Data Analysis Techniques

This paper documents the development, deployment, and assessment of an engine diagnostics capability on school buses, utilizing built-in emissions monitoring capabilities in a telematics device to bring out diagnostic insights around the school bus concerning high emissions for proactive, evidence-based, and preventive maintenance actions to improve the health of the engine and also set up predictive maintenance strategies. The preliminary analysis shows the capability of the system in collecting emissions data and relating the emissions data with other engine parameters to bring out meaningful insights into the health of the engine and also the potential causality for high emissions. Timely actions in the proactive and preventive stages help to curtail the high emissions-related operations, and save fuel costs, along with the environment-related savings on greenhouse gas emissions. The system sets the foundation for high-stakeholder collaboration in the context of utilizing predictive maintenance actions to design holistic preventive maintenance strategies. To harness the full potential of the data, to further enhance the high-impact economic, environmental, and stakeholder-based benefits, and to understand other higher-level aspects and requirements associated with the data, comprehensive data analysis techniques were used, including significant data soundness, completeness, and limitations checks, relationships, drivers, and causality analysis through correlation analysis and regression analysis, data visualization analysis through matrix-based plots, 3D and multi-dimensional plots, and drill-down factors to a variable to further investigate, compare, and match broad zones. The results show significant diagnostic capability in further harnessing the potential with more industry-specific key performance metrics for predictive, condition-based, and overarching enterprise maintenance applications. Since there are also bound to be performance issues in real-life conditions and the use of engines, some of the use cases get limited by this general capability at the outset. The further capability provided by monitoring requires one or more of the restrictions such as the capability of the streaming approach for direct diagnostic and/or root-caused emissions accounting, real-time analysis or summary statistics within a certain timeframe, adding and/or refining alerts, and thresholding with more industry-specific patterns. These model parameters help in harnessing the maximum potential for optimally operating the current buses. They also help in designing smarter fleets and fuel-efficient telematics systems in the future.

4. Case Studies

4.1 Case 1: Enhancing Powertrain System Reliability in Florida School Bus Fleet Case 1 is a real-world case in which the proprietary approach of predictive maintenance and analytics is successfully employed in a seasoned school bus fleet supporting the public sector. After a series of extensive discussions with district staff, a new shared-service initiative is formulated and scopes a five-year data acquisition project that intends to improve reliability, safety, and vehicle performance, and document fleet operating conditions. The initial rollout is being sustained through meaningful regional cooperation efforts. SDATA operates on 193 buses in the district.
4.2 Case 2: Centralized back-office surveillance helps a school bus operator save on engine and turbocharger warranties Two transit entities in Case 2 use an innovative centralized back-office surveillance program to collect and exchange build and registry firmware data from engines and turbochargers. The vehicles are part of a large-footprint diesel bus fleet operable in a densely populated U.S. metropolitan area. Old data collection methods are costly and do not utilize archival bus data, so this big data approach helps seamlessly increase engine and turbocharger warranty and overall vehicle maintenance usefulness. Additionally, this project improves commercial-grade compliance with standardized rules concerning engine data exchange activity. These discussions have a grassroots inception and include input from automotive manufacturers, exhaust catalytic manufacturers, commercial transit agencies, engine and turbocharger manufacturers, and field application support programs. Additionally, registry intelligence rules are framed for restricted written agreements with a regional builder and a specified economic contingency for the federation of parked bus vehicles anywhere in the United States travel scope. The program is presently rolling out in a limited, scalable series of vehicle overlays and back-office setups.

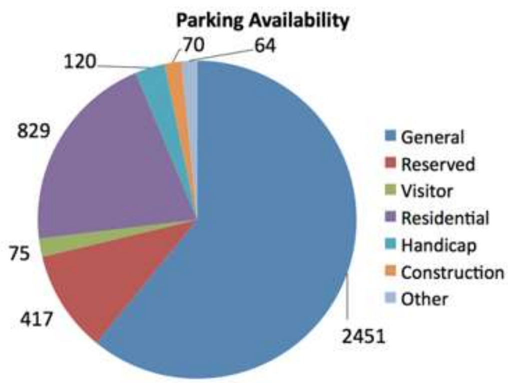

Fig : Analytics in Regular Day-to-day Transportation

4.1. . Implementation of Predictive Maintenance in a School Bus Fleet
As part of field studies on the PRISM research project, new diagnostic and monitoring technologies have been developed and tested in school buses to detect a variety of performance anomalies early and predict remaining useful life. For instance, on each of three buses in a project pilot test, a new synthetic oil monitoring sensor was used to detect oil deterioration caused by fuel soot in the lubricating oil sooner than commercial sensors for heavy-duty vehicles. Real-time monitoring can facilitate changes of oil when it is still usable and thus help prevent subsequent engine problems. New software and a remote telemetry link have also been developed for early fault detection and diagnosis of the transmission and other bus systems. The real-world practical exploitation of diagnostic and prognostic capabilities in school buses calls for the development of a tiered maintenance system based on sensor outputs and prognostics. The implementation of continuous diagnostic and monitoring in school buses can be challenging due to the variations in the capabilities of various fleets' maintenance programs. As a result, a tiered approach to predictive maintenance seems most appropriate. First, some fleet owners have contracts with original equipment manufacturers for warranty coverage or performance monitoring services, so buses can be more easily serviced at the equipment suppliers or original equipment manufacturers' dealers than in others. Reliable maintenance can also be provided in some fleets, but probably not with the real-time online diagnosis and prognostics possible with the real-time onboard technologies available.

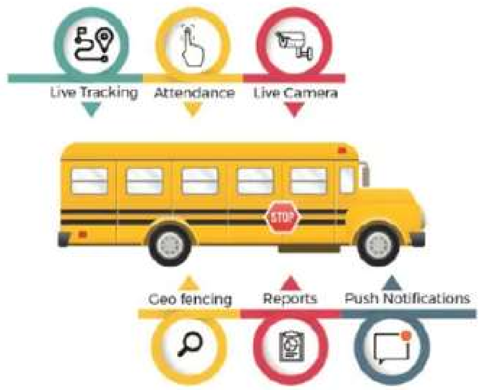

Fig 4 : Predictive Maintenance in a School Bus Fleet

5. Results and Discussion

For the fleet, data-driven analytics enable discovery rather than selectivity and assumption. They can demonstrate the complexity of student transportation, creating a platform for innovation. Robust and predictive school bus maintenance presents a fruitful area for novel thinking and practice, beneficial to both the fleet's dedicated professional staff and the broader analytics community. This paper validates the research's methodology and demonstrates circuit performance gains at near-zero specifically targeted parking events. Energy benefits are achieved by identifying specific areas of noise in high-rev parking and proposing remedies to mitigate the negative environmental impacts of the powertrain's stabilizing operation. These predictively generated suggestions include best practices for shutting down the engine or achieving fuel-efficient idling states that provide a broader benefit over time with best overall practice. An adaptive, incremental, overall engine performance improvement realizing additional ancillary system advantages is also proposed for future research. Technology exists to save more fuel than current hybrid models exploit, but to make school transportation resources even more productive, more sophisticated approaches are required. With aging fleets serving a notably high annual vehicle duty cycle in many districts as a primary mode, the use of advanced analytics such as those supporting condition-based predictive maintenance as part of long-term shop planning can be meaningful. Fleet-wide integration of these practices across the industry can add to system resiliency during future maintenance labor challenges. A significant benefit of these analyses is their support for demand management, improving overall planning consistency, and making school transportation a prime consideration in research funding that targets infrastructure inefficiencies experienced by an imperative transportation market.

Equ 3: Beta distribution

$$\begin{aligned} f(x;\alpha,\beta) &= \mathrm{constant}\cdot x^{\alpha-1}(1-x)^{\beta-1} \\ &= \frac{x^{\alpha-1}(1-x)^{\beta-1}}{\int_0^1 u^{\alpha-1}(1-u)^{\beta-1}\,du} \\ &= \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\,x^{\alpha-1}(1-x)^{\beta-1} \\ &= \frac{1}{\mathrm{B}(\alpha,\beta)}x^{\alpha-1}(1-x)^{\beta-1} \end{aligned}$$

5.1. Impact of Predictive Maintenance on Engine Performance

A possible perception of school bus fleet managers, when deciding on the importance, necessities, and potential gains that they might achieve by using predictive maintenance for engines utilizing real-time engine performance and driving conditions, is the possibility of extending maintenance cycles. On one hand, delaying or even removing the less frequent planned repair and maintenance intervention cycles can result in an overall gain, given that buses can remain available for pupil transportation for a longer time, leading to cost reduction savings on labor, spare parts, and contracted maintenance. This also allows school bus mechanics to better manage their actual workload promptly and respond more effectively to the exact requirements of use. On the other hand, postponing periodic interventions can contribute to reducing bus operation times just after the planned maintenance, thus affecting pupil transportation services offered.

Additionally, a popular perception for ensuring the overall operation and preservation of the school bus is that, with longer and more stringent maintenance requirements, the engine takes precedence due to the exponential consequences on the rest of the system. Bearing in mind the importance of the school bus engine, the school bus engine emission checkboxes were discussed in the previous section of this research. From the above, it can be inferred that the effective application of optimized predictive maintenance, involving data-driven analytic techniques on the school bus engine, can maximize all of the aforementioned benefits, substantially reducing no-found failures or the application of inefficient preventive maintenance in the interim stages of a maintenance program, and managing the costs associated with asset failures, establishing communication-related to failure probability, and the likelihood of the source of the failure. Would this trend involve, initially, only buses on the way to becoming autonomous, given the specificities and potential reduction of costs for insurance companies offering insurance?

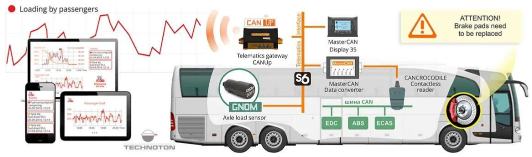

Fig 5: Predictive Maintenance on Engine Performance

6. Conclusion

Conclusion It is estimated that American children make about 180 million trips to and from school on buses. The school bus has, over the years, evolved drastically. Its role is no longer limited to transportation. To better manage its growing list of responsibilities, we must improve how the bus behaves. While the overall quality of diesel has also gone through vast improvements and even the bus building industry has made safety improvements over the past decade, the engine, which is vital to the operation, only gets the attention of its life cycle during breakdowns. This is the main motivation of my research: we cannot see interruptions. If we can predict the engine performance and avoid breakdowns, we are not only avoiding the obvious, but we are also keeping our carbon footprint in check.

As we move into an era with an increasing demand for electric buses, in developing countries, diesel is still the king of the road in the transportation of goods and people. Buses are known for the work they do on the road with the passengers and the areas around them filled with noxious fumes. Bus initiatives are limited to replacing diesel with electric. The quality of life and safety of the school bus crew is still secondary to the huge push that electric buses are receiving. What I'm proposing here is a predictive maintenance tool. This attention to bus health can be translated into healthier and safer buses for the students, noise pollution reduction for the bus operators, and significant help in reducing the fatalities and injuries due to accidents caused by buses, mostly those that happen due to structural failures, including the breaking of vital engine components, like the piston rod. This work is intended to help and support bus fleet operations and make them more sustainable.

6.1. Future Trends

Improvements in fuel economy and reduced emissions technology are expected to include electric buses, compressed natural gas buses, and other alternative power source buses. The move to alternative energy will change some of the maintenance requirements in terms of the drive system, the brake system, and the function of the buses. The results in this study suggest that predictive maintenance may be applied with valid and useful results in these new and emerging technologies. Possibilities for future use and improved job performance include searching for additional critical sensors to monitor some of the other decisions and areas of known interest for each of the districts, as well as identifying a critically important disaster recovery backup system in the district to prevent any future outages, such as the one that occurred during project discussions.

Other areas of interest include the trend-setting application of business intelligence and data analytics in other service industries and how to convert more preventative and annual maintenance into predictably timed, just-in-time predictive maintenance situations. Maintaining an optimal maintenance schedule at all times will free up workers who previously were waiting for their buses to be serviced, as well as ensure that the fleet is running as efficiently as possible. By maintaining the optimal balance of service and downtime through predictive maintenance analytics, state motor pools and school districts will minimize the wear and tear on their assets and extend the useful life of their vehicle assets.

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