DataEdge: Transforming Public Transit with Scalable Edge AI for Predictive Bus Maintenance

Table of Contents

Contents

SBA Company Registry Confirmation

SBIR.gov SBC Registration

SBC Control ID:	SBC_001826175		
Company Name:	AI POW LLC		
Address:	2605 Somerton Ct		
City:	College Station		
State:	TX	**Zip:**	77845-7466
EIN (TIN):	842025137	**DUNS:**	117371359
Company URL:			
Number of Employees:			3
Is this SBC majority-owned by multiple venture capital operating companies, hedge funds, or private equity firms?			No
What percentage (%) of the SBC is majority-owned by multiple venture capital operating companies, hedge funds, or private equity firms?			0.00%

SAM Registration Confirmation

SAM.GOV®

AI POW LLC

Unique Entity ID **HP49U28BVZJ3**	CAGE / NCAGE **8S2D4**	Purpose of Registration **All Awards**
Registration Status **Active Registration**	Expiration Date **Mar 13, 2025**	
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Business Information

Doing Business as **(blank)**	Division Name **Ai Pow Llc**	Division Number **AI POW LLC**
Congressional District **Texas 10**	State / Country of Incorporation **Texas / United States**	URL **(blank)**

Registration Dates

Activation Date **Mar 15, 2024**	Submission Date **Mar 13, 2024**	Initial Registration Date **Oct 29, 2020**

Entity Dates

Entity Start Date **Jun 5, 2019**	Fiscal Year End Close Date **Sep 30**

Immediate Owner

CAGE **(blank)**	Legal Business Name **(blank)**

Highest Level Owner

CAGE **(blank)**	Legal Business Name **(blank)**

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Profit Structure **For Profit Organization**		

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Self Certified Small Disadvantaged Business
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Financial Information

Accepts Credit Card Payments **Yes**	Debt Subject To Offset **No**
EFT Indicator **0000**	CAGE Code **8S2D4**

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Service Classifications

NAICS Codes

Primary	NAICS Codes	NAICS Title
Yes	**513210**	**Software Publishers**
	518210	**Computing Infrastructure Providers, Data Processing, Web Hosting, And Related Services**

Product and Service Codes

PSC	PSC Name
H370	**Inspection- Automatic Data Processing Equipment (Including Firmware), Software, Supplies And Support Equipment**

Disaster Response

This entity does not appear in the disaster response registry.

DataEdge: Transforming Public Transit with Scalable Edge AI for Predictive Bus Maintenance

1 Identification and Significance of the Problem or Opportunity

U.S. public transit agencies devote a substantial share of resources to fleet upkeep. Vehicle maintenance alone accounts for about 16–21% of total operating expenses (over $8 billion annually in 2021) [1]. Despite this investment, bus fleets still experience frequent mechanical failures. For example, Washington D.C.'s Metrobus fleet reported a mean distance between failures of only 6,300–8,300 miles in recent years [2], leading to multiple breakdowns per bus annually, underscoring the need for more proactive maintenance.

Despite substantial investments, these frequent mechanical failures persist largely because the following reasons: **manual troubleshooting** in large fleets is highly variable, as it hinges on individual mechanics' expertise—leading to inconsistent diagnostics, longer repair times, and even repeat failures [3]. While **AI-driven predictive** maintenance can potentially reduce costs by around 20% and halve unscheduled breakdowns, adoption remains slow due to transparency issues [4], particularly because **technicians** distrust black-box recommendations, **managers** struggle to plan effectively when AI outputs lack context, and **executives** are hesitant to invest without clear cost-avoidance data. As a result, agencies risk underutilizing AI despite its predictive accuracy—demonstrating that Explainable AI is essential for building trust and providing actionable insights across technicians, managers, and decision-makers.

To address the limitations of both manual troubleshooting and opaque AI models, **our team introduces DataEdge, An Explainable AI (XAI) Solution for Scalable Predictive Maintenance.** Unlike conventional black-box AI, DataEdge aims to provide *interpretable insights* allowing **technicians** to see which sensor anomalies trigger failure predictions, giving them a map to help them diagnose issues with clarity and accuracy. For **maintenance managers**, DataEdge translates AI-driven alerts into structured recommendations, that can allow them improve workforce allocation and inventory management. At the **executive level**, its transparent cost-benefit analyses ensure AI investments align with operational goals. By embedding explainability at every level, DataEdge aims to enhance trust, accelerates AI adoption, and delivers measurable reductions in downtime and maintenance costs.

As part of this proposal, we have engaged key stakeholders to refine our **AI-driven predictive maintenance approach**. **Mr. Chunyu Lu from Traf-O-Data** will facilitate access to **BEB 40FC bus data** and provide **operational feedback** throughout Phase I. **Dr. Yunlong Zhang from Texas A&M University** will be our point of contact **with transportation agencies at Texas A&M University's transit** to validate predictive models using a **BEB 40FC** bus, our testbed for real-world evaluations. Additionally, **Dr. Yunpeng "Jack" Zhang, Director of CYBER-CARE at the University of Houston**, will contribute his **expertise in cybersecurity, artificial intelligence, and the Internet of Things (IoT)** to strengthen DataEdge's predictive maintenance framework. We also extend our gratitude to **Mr. McCambridge Andrew, Maintenance Training Instructor at San Mateo County Transit District**, for his valuable input on **On-Board Diagnostics II (OBD2) bridge integration**, ensuring alignment of this proposal with real-world troubleshooting requirements. Beyond public transit applications, **DataEdge has strong potential for industry adoption**. **Trane**, a leader in **HVAC and cold chain logistics**, has provided a letter showing their interest in leveraging DataEdge for **truck-mounted refrigeration unit maintenance**. This expansion would enhance **temperature stability, reduce spoilage risks, and improve operational efficiency**, demonstrating DataEdge's scalability across **transportation and logistics sectors**. Finally, based on insights from our stakeholder interviews, the table below summarizes the advantages of our proposed solution compared to existing approaches.

Aspect	**Manual Troubleshooting**	**Current AI-Based Predictive**	**Proposed DataEdge XAI-Powered Predictive**
Maintenance Strategy	Reactive "fix after failure" approach	Predictive alerts with limited explainability	Predictive alerts with interpretable justifications, improving operator trust
Diagnosis Approach	Relies on human troubleshooting expertise and OBD2 scans	AI detects patterns but lacks transparency	AI explains flagged anomalies with root cause analysis and OBD2 insights

Cost Efficiency	High costs due to emergency repairs	Moderate savings but underutilized due to lack of confidence in AI	Maximized cost efficiency by integrating AI insights into decision-making
Decision-Making Support	Fleet managers rely on experience-based judgment	AI models provide alerts but require manual interpretation	AI-driven insights with explainability to support executive-level decisions
Workforce Readiness	Dependent on technician expertise and experience	Requires AI model monitoring but lacks structured training	Workforce training on AI for long-term adoption and integration

Finally, our team proposes to kickstart the DataEdge development upon our team's work in embedded systems and time-series anomaly detection [5, 6] which has already been used in industrial manufacturing scenarios and helped reduce the technical risk of the more complex system proposed here.

2 Phase I Technical Objectives

Time-series data, composed of sequential data points collected over time, is crucial for tracking trends, detecting patterns, and making predictions in dynamic systems. In public transit, vehicles continuously generate vast amounts of time-series data, capturing critical operational metrics. Effectively leveraging this type of data is essential for the monitoring of operating conditions and the detection of potential issues conditions across the vehicle systems.

Our team has extensive preliminary work in time-series data anomaly detection [6] and edge computing. Our work on object detection for edge computing [7] investigated lightweight computing architectures optimized for environments with limited computational memory (we provide more information in subsection 4.1). However, adapting these solutions to public transit fleet environments introduces new technical challenges. Unlike previous use cases, vehicle systems are highly complex and interconnected, generating multiple time-series data streams from different components, such as engine performance, fuel efficiency, tire pressure, and even air condition system's (HVAC) status. **This complexity requires predictive models that can analyze multiple data channels holistically to detect interdependent failures rather than treating each channel in isolation**. Additionally, to function effectively on moving vehicles, edge devices must operate independently in resource-constrained environments, which may lack internet connectivity, limited computing power, and noisy data sources. Furthermore, vehicle failures often arise from intricate system interactions rather than isolated anomalies, requiring models to generate clear, interpretable results that offer insights for fleet operators. Without explainability, even accurate predictions may not be useful for decision-making, limiting adoption and effectiveness in AI-driven predictive maintenance.

To address these problems, we propose a comprehensive AI-driven predictive maintenance solution that integrates edge computing and deep learning algorithms with strong interpretability. As presented in Fig. 1, our approach is structured around three key technical objectives in **(1) we will develop an easily deployable edge device** designed to operate within transit fleets, which will be capable of collecting time-series data from various components across buses and running AI models locally, in **(2) we will develop a deep-learning-based anomaly detection framework** that not only identifies potential mechanical failures and inefficiencies within vehicles but also incorporates Explainable AI techniques to provide interpretable insights into detected anomalies, enabling fleet operators to understand root causes and make data-driven maintenance decisions, and **(3) we will design and deploy DataEdge** as a **modular platform**, enabling **rapid iteration and deployment** based on a **lean build-test-learn methodology**. This modularity will allow us to quickly integrate new sensors, adapt AI models, and refine predictive maintenance algorithms in response to real-world feedback from transit agencies. By continuously monitoring system performance and incorporating user insights, we will accelerate the development cycle, ensuring that DataEdge evolves to meet the dynamic operational needs of public transit fleets. This approach will facilitate **seamless upgrades**, reduce downtime associated with hardware or software modifications, and support the scalable adoption of AI-driven predictive maintenance across diverse transit environments.

Technical Objective 1: Edge AI for Real-Time Anomaly Detection.

This objective aims to develop a highly adaptable edge AI system for real-time anomaly detection and predictive maintenance in transit fleets. To kickstart our work, we will build upon our existing advance-

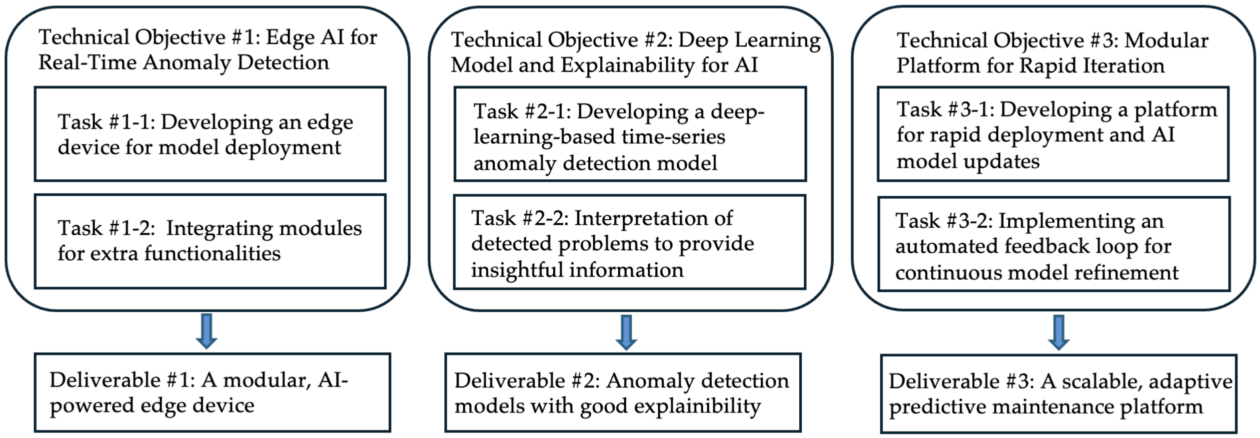

Figure 1: Overview of DataEdge's Technical Objectives, Tasks, and Deliverables.

ments in edge computing [7, 8] and anomaly detection [5], extending these capabilities to broader fleet diagnostics. This approach will enable optimized performance in resource-constrained environments, addressing a wider range of transit fleet operational challenges while ensuring scalable solutions.

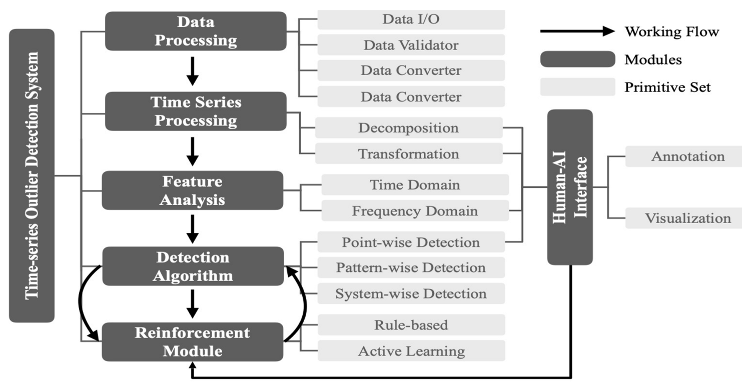

Figure 2: The diagram of the proposed time series outlier detection system.

To achieve this, we will customize a (1) a low-power, embedded edge device optimized for seamless deployment on BEB 40FC buses and (2) integrate compatibility with the OBD2 (which Parameter IDs are presented in Tab. 2), the standard protocol for diagnostics in our transportation partner's transit buses. This device will host six main computational blocks, as seen in Fig. 2, designed to enhance anomaly detection in time-series data. The **data preprocessor** standardizes and processes input data from various sources, ensuring validation, imputation, and conversion. The **time series processor** applies smoothing and transformation techniques to handle trends and seasonality in the data. The **feature analyzer** extracts meaningful insights from time-series data across temporal, frequency, and latent feature domains. The **detection modules** employ state-of-the-art machine learning techniques, including traditional methods like isolation forests and deep learning models such as Long Short-Term Memory autoencoders and Generative Adversarial Networks, to identify anomalies. Since labeled outliers are often unavailable initially, the **reinforcement module** integrates domain expertise through active learning and rule-based modeling to refine detection models. Lastly, the **human-AI interface** provides a graphical interface, enabling users to design, visualize, and fine-tune the outlier detection pipeline interactively.

By integrating our prior work in edge AI, time-series anomaly detection, and system modularity, we aim to deliver a robust and scalable edge computing solution for transit fleets, as presented in Fig. 3. This system will lay the foundation for real-time, AI-powered diagnostics, improving fleet reliability, reducing maintenance costs, and enhancing operational efficiency.

Technical Objective 2: Deep Learning for Time-Series Anomaly Detection and Explainability for AI

Typically, outliers could indicate the rarity of an observed pattern or a low probability that a given instance appears, but those outliers do not necessarily mean problems that need immediate attention. Without providing rationale behind detection results, it is very challenging for technicians and other end-users to understand why a particular bus needs maintenance, impeding users from troubleshooting a problem by trusting the models or taking further actions against the detected outliers.

To address this problem, we have studied various interpretable machine learning models in multiple fields of application. In [9], the authors have proposed a one model-agnostic outlier interpretation method to address the outlier detection problem by resolving outliers' local context. Specifically, the outlier inter-

PID	Parameter Name	PID	Parameter Name
0C	Engine RPM	0D	Vehicle Speed
05	Engine Coolant Temperature	0F	Intake Air Temperature
10	Mass Air Flow (MAF) Sensor	11	Throttle Position
1F	Engine Run Time Since Start	2F	Fuel Level
33	Barometric Pressure	42	Control Module Voltage
4C	Commanded Throttle Actuator	51	Fuel Type
5C	Engine Oil Temperature	5E	Fuel Injection Timing
61	Driver's Demand Torque	62	Actual Engine Torque
63	Engine Reference Torque	7C	Diesel Particulate Filter (DPF) Temperature

Table 2: List of OBD2 Parameter IDs (PIDs) and Corresponding Vehicle Data Points. These parameters provide real-time diagnostic and performance information from a vehicle's onboard computer, essential for monitoring engine health, fuel efficiency, and operational status.

pretation is defined with three aspects: abnormal attributes, outliers score, and the outlier's context clusters. Researchers have distilled interpretation from a series of classification tasks between normal class and outlier class. After interpretation, we have also shown that prior domain knowledge can be incorporated to adapt outlier detection results to different applications. Another explainable recommender systems framework was proposed in [10] to overcome the representation entangling problem in deep neural models. This work's main idea includes disentangling the interactions between latent representations in different neural layers, identifying multiple semantic factors from data, and dividing latent representations into segments according to their information source. **To add AI intepretability to our proposed DataEdge platform**, we propose a novel (1) deep-learning based time-series anomaly detection model with graph convolution layers and segment the layers to force each layer to focus on different data aspects for interpretability. Although this work focuses on the recommendation system, we formulate the outlier detection problem as the recommendation system because the algorithm's goal is to recommend the most anomalous data point from a pool of data points.

The two previous works focus on what to provide as the interpretation and how to interpret the outlier detection model. Our goal is to (2) leverage the benefits of both methods and to develop a unified interpretable outlier detection framework. Notably, we will follow the interpretation definitions of contextual outliers [9] to define and segment [10] the neural network layers and modify the learning objectives from item recommendation into outlier detection. The developed framework will also be implemented into our BOD2 data ingestion systems to provide interpretations for various scenarios of outlier detection.

At the onset of this Phase 1 our team will have integrated explainable AI in our anomaly detection model, depicted a 'Contribution scores' in Fig. 4. With this, our solution will provide mechanics, fleet managers, and executives with the tools needed to make insightful, data-driven decisions, ultimately providing a measurable key results 3.1 that will provide clear evidence of an improved maintenance efficiency and operational costs reduction.

Technical Objective 3: Modular Platform for Rapid Iteration in Predictive Maintenance

To ensure continuous improvement and adaptability in predictive maintenance, we will develop (1) DataEdge, a modular platform that supports rapid iteration and deployment based on a lean build-test-learn methodology. DataEdge will be designed to seamlessly integrate new sensors, update AI models, and refine anomaly detection algorithms in response to real-world data and user feedback from transit agencies.

To enable efficient and flexible system evolution, we will implement (2) an automated feedback loop that continuously collects system performance metrics and operator insights to inform iterative model updates. This mechanism will support adaptive AI refinement, ensuring that the predictive maintenance framework evolves alongside changing fleet conditions and technological advancements. Additionally, we will conduct bi-weekly meetings with key stakeholders, including transit agencies and fleet operators, to gather feedback, assess system effectiveness, and prioritize feature improvements. These structured discussions will reinforce a user-driven approach to development and ensure that the platform remains aligned with operational needs.

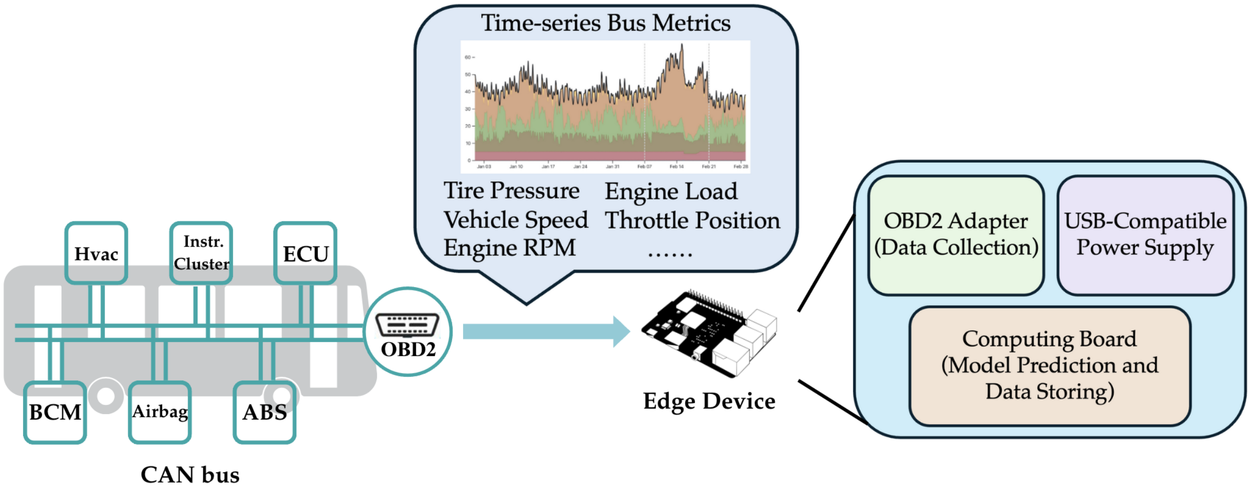

Figure 3: Technical Objective 1. **DataEdge Edge Computing Architecture for Predictive Maintenance.** This diagram illustrates the integration of DataEdge's edge AI system with a **BEB 40F battery-electric bus** via an **OBD2 interface** connected to the vehicle's **CAN bus network**. The edge device collects **time-series bus metrics** such as **tire pressure, engine RPM, vehicle speed, engine load, and throttle position**, enabling real-time anomaly detection and predictive maintenance. The modular edge computing system includes an **OBD2 adapter for data collection**. **Our computing board, which is based on a Broadcom BCM2712 quad-core Arm Cortex-A76 processor @ 2.4GHz with 8GB of RAM and 64GB of SSD storage,** processes data locally, running predictive AI models and storing results for fleet-wide maintenance optimization. This architecture ensures **scalable, real-time diagnostics**, improving vehicle reliability, reducing unexpected failures, and lowering maintenance costs.

2.1 Potential Risk and Mitigation Plan

One significant risk lies in the potential for **data quality issues** stemming from diverse sensor variations within the bus. Inconsistent or noisy data from aging sensors could compromise the accuracy of AI models, leading to false positives or missed failure predictions. To mitigate this, the DataEdge system will implement real-time data validation and anomaly detection at the edge device level, flagging suspect sensor readings for review. Additionally, our modular platform supports continuous sensor calibration and integration of new data streams, enabling adaptation to a wide range of vehicle configurations and sensor technologies while also incorporating additional sensor readings to compensate for a faulty sensor.

Another crucial risk is the potential for **limited computational resources on edge devices**, which could hinder the real-time performance of complex AI models. Processing power, memory, and energy constraints on transit vehicles could impact the speed and accuracy of anomaly detection, especially when analyzing multiple interdependent data streams. To address this, we will optimize our deep learning models for edge deployment using techniques like quantization and pruning. Our TDEngine time-series database will efficiently manage local data storage, prioritizing critical parameters for analysis. The integration of our system is designed to seamlessly integrate with existing vehicle infrastructure which means limited need for on-vehicle energy consumption.

Finally, **user adoption challenges** present a risk if maintenance staff are skeptical of AI-driven recommendations or lack the training to effectively interpret and act upon system insights. Resistance to change and a preference for traditional troubleshooting methods could limit the impact of even the most accurate predictive models. To mitigate this risk, we will further pair scientific R&D on explainable AI, along with a **build-measure-learn feedback loop** (shown as Continous 'lean-methodology' innovation in our Project Timeline 5) to provide corresponding engineering solutions in our system to address the user adoption challenge. Specifically, we will expand our findings into our system by following our previous research on explainable contextual outlier detection following a lean methodology approach.

3 Phase I Work Plan

Phase I of this project will focus on developing, testing, and validating the DataEdge platform for AI-driven predictive maintenance in public transit fleets as follows:

Project Timeline and Deliverables. The Phase I R&D effort will be structured into three main phases over a **six-month period**, with each phase aligning with a core project objective:

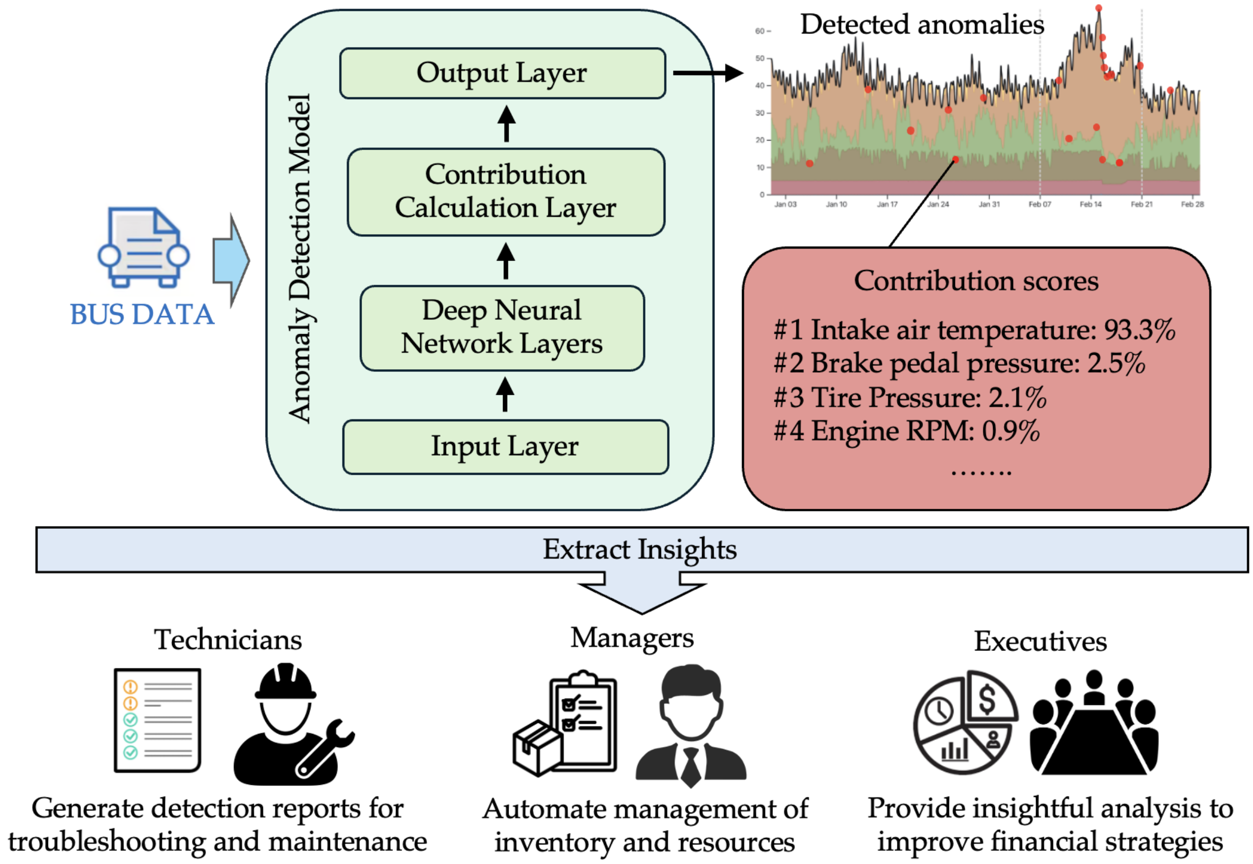

Figure 4: Technical Objective 2. **Explainable AI-Powered Anomaly Detection and Decision Support in DataEdge.** This diagram illustrates **DataEdge's predictive maintenance workflow**, from **bus data ingestion** to **anomaly detection** and **stakeholder-specific insights**. The **anomaly detection model** processes key vehicle metrics through **deep neural network layers**, identifying anomalies and assigning **contribution scores** to critical parameters such as **intake air temperature, brake pedal pressure, tire pressure, and engine RPM**. A **contribution calculation layer** ensures **explainability** by quantifying the impact of each factor on detected anomalies. Insights extracted are tailored for different stakeholders: **technicians** receive **troubleshooting reports**, **managers** optimize **inventory and resource management**, and **executives** gain **data-driven analysis** to refine **financial and operational strategies**. This architecture enhances **transparency, efficiency, and trust** in AI-powered predictive maintenance for transit fleets.

Months 1–2: Edge AI for Real-Time Anomaly Detection (Technical Objective 1) Develop and optimize edge AI for real-time anomaly detection. Integrate sensors and ensure efficient data processing. Validate performance through lab testing.

Months 3–4: Deep Learning Model and Explainable AI (Technical Objective 2) Develop Explainable AI framework that leverages feature attribution to enhance predictive maintenance. Implement techniques that identify and highlight key factors contributing to detected anomalies, ensuring stakeholders can interpret and act on AI-driven insights.

Months 5–6: Modular Platform for Adaptive Learning and Rapid Iteration (Technical Objective 3) Deploy a modular platform DataEdge that integrates feature attribution-based AI updates and sensor data for predictive maintenance. Refine system capabilities through bi-weekly stakeholder feedback, ensuring usability and trust across technicians, managers, and decision-makers.

A clear overview of this timeline is illustrated in Fig. 5.

3.1 Expected Phase I Deliverables

By the end of Phase I, we expect to have the following Deliverables: **Deliverable 1**, A validated **edge AI-based time-series anomaly detection framework** for vehicle diagnostics, ensuring interpretability in predictive maintenance. **Deliverable 2**, A functional **DataEdge prototype**, integrating **Explainable AI** for

PROJECT TIMELINE start August 2025 - end January 2026			Months					
Technical Objectives	**Tasks**	**Team**	M1	M2	M3	M4	M5	M6
Deliverables				D1		D2		D3
TO#1: Edge AI for Real-Time Anomaly Detection	Development of edge device for model deployment	AC, DD						
	Functional modules integration for extra functionaries	DD						
TO#2: Deep Learning Model and Explainability for AI	Time-series anomaly detection model development	AC, XH						
	Interpretation of problems detected by AI model	AC, XH						
TO3#: Modular Platform for Rapid Iteration	Development and deployment of DataEdge platform	AC, DD						
	Implementation of automated feedback loop	DD						
Continous 'lean-methodology' innovation	Build	AC						
	Measure	AC						
	Learn	AC						

AC: PI Alfredo Costilla-Reyes	D1	**A modular, AI-powered edge device**	**Notation:**
XH: Dr. Xia (Ben) Hu	D2	**Anomaly detection models with good explainibility**	D **Deliverable**
DD: Daniel Deng	D3	**A scalable, adaptive predictive maintenance platform**	TO# **Technical Objective**

Figure 5: DataEdge's Timeline for Phase I

anomaly detection, deployed and tested in a transit fleet environment to assess interpretability, usability, and trust. **Deliverable 3**, A refined **Phase II roadmap**, incorporating insights from fleet testing, stakeholder feedback, and performance evaluations to enhance AI transparency and adoption.

Key Metrics. We will use the **BEB 40FC's Foothill Transit Battery Electric Bus Evaluation: Final Report** [11] as our benchmark vehicle model and define the following key metrics to evaluate the impact of our predictive maintenance system: (1) **Availability Improvement**: The current availability of BEB 40FC buses is 76.1%. Our goal is to increase this to at least **85%**, reducing downtime through proactive failure detection and optimized maintenance scheduling. (2) **Miles Between Roadcalls (MBRC)**: The MBRC for BEB 40FC is currently 8,053 miles. We aim to extend this to at least **10,000 miles**, minimizing unexpected breakdowns through anomaly detection and predictive diagnostics. (3) **Maintenance Cost per Mile Reduction**: The current maintenance cost per mile for BEB 40FC is \$0.564. Our system aims to reduce this to **\$0.50** by optimizing maintenance schedules and preventing emergency repairs.

4 Related Research or R&D

Explainable AI for predictive maintenance is rapidly expanding in transportation, aligning with DataEdge's goals. **The MetroPT dataset (2022)** offers a key benchmark for public transit maintenance, featuring sensor data from metro vehicles with recorded failures. Studies using this dataset have tested both rule-based systems and deep learning autoencoders, yet researchers note "there is a vast space to improve accuracy and explanation" [12], reinforcing DataEdge's focus on interpretable predictive models. This trend toward hybrid methods that balance accuracy with transparency underpins DataEdge's combination of **feature attribution, rule-based models, and case-based reasoning.** *As specialized datasets emerge, ongoing research highlights the need for interpretable solutions in public transit maintenance, providing a strong scientific foundation for DataEdge's Explainable AI architecture.*

Edge AI technologies enable **real-time anomaly detection** without constant cloud connectivity, central to **DataEdge's operational model**. Recent patents have introduced systems for detecting behavioral anomalies among fleets of connected vehicles, using machine learning to generate behavioral profiles that can identify potential maintenance issues before they cause breakdowns [13]. The Edge AI approach enhances vehicle predictive maintenance through advanced in-vehicle processing, where trained AI models sent over-the-air to vehicles identify anomalous data patterns prior to transmissions. In a similar way, [14] the authors demonstrated a federated learning model for real-time predictive maintenance. TIP4.0 used compressed deep-learning models to enhance industrial equipment monitoring while maintaining accuracy [15]. *This aligns with DataEdge's goal of processing sensor data locally on transit vehicles, reducing latency for critical fault detection while preserving bandwidth.*

IoT-based predictive maintenance enhances fleet reliability through cloud analytics. The Car e-Talk system collects vehicle sensor data for anomaly detection and preventive maintenance [16]. Ford's cloud-based predictive maintenance patent applies federated learning to estimate part lifespans [17]. *By integrating edge analytics, DataEdge improves fleet-wide predictive accuracy and maintenance planning.*

Commercial solutions: Table 3 presents a comparative analysis of AI-based predictive maintenance solutions for public transit fleets, highlighting key strengths and limitations. **Zonar** and **Geotab** offer telematics-based diagnostics but rely on fault-code monitoring with limited AI explainability. **Vontas** and

Clever Devices provide predictive maintenance and remote fleet monitoring but lack advanced AI-driven insights. **Samsara** leverages cloud-based analytics but depends on threshold-driven AI, while **Optibus** focuses on AI-powered route optimization rather than predictive maintenance. **Predii** applies NLP-based diagnostics for automotive repair but is not specialized for public transit. In contrast, our DataEdge proposal differentiates itself with Explainable AI, providing interpretable root-cause insights. Our proposed edge-computing design enables real-time anomaly detection onboard vehicles, reducing latency and data transfer costs. Unlike broad telematics or enterprise asset management solutions, DataEdge is transit-focused, integrating industry-standard sensor protocols OBD2 (Phase I), and J1939 (Phase 2) with user-friendly insights. Its modular and scalable architecture ensures adaptability to emerging technologies, making it a future-proof solution in a market dominated by black-box AI and rule-based systems.

Table 3: Market Analysis of AI-based Predictive Maintenance Solutions for Public Transit Fleets

Solution	**Technology Approach**	**Strengths**	**Limitations**
Zonar [18]	Telematics-based diagnostics	Established customer base	Limited AI explainability
Vontas [19]	Predictive maintenance software	Integrated transit solutions	Early-stage AI features
Clever Devices [20]	Remote fleet monitoring	Strong presence in public transit	AI-based insights are partial with limited explainability
Samsara [21]	Cloud-based analytics	Scalable IoT integration	Threshold-driven AI, no insights
Geotab [22]	Add-on analytics modules	Extensive data integrations	Requires external AI solutions
Optibus [23]	AI-driven route optimization	Strong scheduling automation	Limited predictive maintenance capabilities
DataEdge	Edge AI for real-time anomaly detection	Focus on Explainable AI insights	New entrant. Lower market recognition

4.1 Our Preliminary Work

Our team proposes to build upon our preliminary work from [7] as a foundation for developing an embedded edge device optimized for seamless deployment on transit buses. The system described in [7] was designed to enable real-time object detection on low-power hardware, integrating a deep neural network with a camera and display on the MAX78000 edge accelerator. This work demonstrated the feasibility of running efficient deep learning models on resource-constrained devices while maintaining real-time processing capabilities. Notably, [7] **achieves a 91.9 ms inference time with an energy consumption of 1.845 mJ**, making it highly efficient for real-time applications.

Expanding on this foundation, we will adapt the system in [7] to support anomaly detection in transit buses by optimizing its hardware and software for real-time monitoring and analysis. The core of this system will be a modular edge device designed to operate with low power consumption while running anomaly detection models efficiently. The device will integrate a sensor suite for collecting critical operational data, a real-time edge processor for on-device inference, and a flexible architecture that allows additional functional components to be incorporated based on the specific needs of this proposal.

By leveraging the lightweight neural network design and quantization techniques from [7], we will develop models that can process sensor data in real time while operating within the computational constraints of an embedded system. The optimized pipeline for model training, quantization, synthesis, and deployment from [7] will serve as a blueprint for refining the anomaly detection framework, ensuring that it remains efficient and adaptable. To further enhance deployment efficiency, **we estimate that DataEdge can be directly wired to a bus' standard USB port**, eliminating the need for external power sources. **We do not plan to use batteries in Phase I**, ensuring a simplified and maintenance-free power solution.

5 Key Personnel and Bibliography of Directly Related Work

PI Alfredo Costilla-Reyes is the Chief Technology Officer at AIPow LLC, a spin-off from Rice University, and a former investor partner at the Kirchner Group. He holds a doctorate in Electrical Engineering from Texas A&M University and has earned certificates in Entrepreneurship and Technology Commercialization from Mays Business School. Dr. Costilla-Reyes has led venture capital-funded projects in embedded software and systems, including future agriculture, battery-less wearable consumer electronics, application-specific integrated circuits, and wireless IoT systems. **The PI has a proven track record of successfully delivering commercially viable technologies through prior SBIR support**, demonstrating both the technical execution and managerial infrastructure required for federal grants. He was awarded NSF SBIR Phase I (Award #2136679) for *A Hardware-Aware AutoML Platform for Resource-Constrained Devices* [5], followed by NSF SBIR Phase II (Award #2335642) [24]. These federal grants exemplify the team's ability to develop innovative AI-driven solutions with real-world industrial applications, and the proposed project builds upon this foundation to enable the rapid, cost-effective, and scalable deployment of on-device AI. Related work (hardware): [7, 8, 25].

Senior Personnel. Xia (Ben) Hu serves as VP of Engineering at AI POW LLC. Dr. Hu is also an Associate Professor at Rice University in the Department of Computer Science and the Director of the Data-to-knowledge (D2K) Lab at Rice Univerity. His highly successful open-source work in machine learning automation and explainability will be essential for him to lead our open-source sandbox efforts. He has published more than 100 papers in major data mining venues. His articles have received seven Best Paper Awards (candidate), and he is the recipient of the JP Morgan AI Faculty Award, the Adobe Data Science Award, and the NSF CAREER Award. An open-source package developed by his group, namely AutoKeras, has become the most used automated deep learning system on Github (with over 8,600 stars and 1,400 forks). Dr. Hu's work on deep collaborative filtering, anomaly detection, and knowledge graphs is part of the TensorFlow package, Apple production system, and Bing production system. Hu's work has been cited more than 13,000 times, with an h-index of 48. He was the conference General Co-Chair for WSDM 2020. Related work (software): [6, 26, 27, 28]

Daniel Deng is a Senior Software Developer with the DataEdge team. He holds a Master of Science in Computer Science from Yale University and previously worked at Microsoft, where he improved meeting analytics for Microsoft Teams by enhancing data processing and visualization, which impacted over 280 million users. He has also contributed to AI research in various labs, focusing on data-driven anomaly detection and predictive modeling. His expertise includes data analytics, data visualization, and building scalable data pipelines, with a strong background in designing reliable data processing systems.

6 Relationship with Future Research and Development

The proposed project, if successful, will establish a foundation for large-scale, real-time predictive maintenance solutions applicable across various industrial and public transportation settings. Phase I will demonstrate the feasibility of integrating advanced time-series at the edge with advanced explainability, while Phase II will focus on scaling the framework to handle complex, real-world deployments in transportation.

6.1 Future Large-Scale AI Model Optimization for Real-Time Predictive Maintenance

A key focus of our Phase II work is optimizing time-series modeling for predictive maintenance. To achieve this, we will implement state-of-the-art deep learning techniques such as Long Short-Term Memory (LSTM) networks, Temporal Convolutional Networks (TCN), and self-supervised learning approaches. These methods will enable our models to learn temporal dependencies within vehicle data streams, allowing for early detection of performance degradation and component failures before they occur.

Another critical aspect of our Phase II research is enhancing predictive capabilities through multi-modal data fusion. By integrating diverse sensor modalities, such as telemetry data (e.g., temperature and voltage) with external environmental factors (e.g., location, weather, and traffic conditions), we aim to improve failure prediction accuracy and reduce false alarms. This fusion of data sources will allow for a more comprehensive understanding of vehicle health and operational conditions.

To ensure scalability and real-time adaptability, our predictive models will be designed to process large-scale streaming data efficiently. The architecture will support real-time updates, online learning, and retraining mechanisms, enabling it to adapt to emerging failure patterns while minimizing latency and computational overhead. By implementing these capabilities, we will improve the robustness of predictive maintenance systems for large transit fleets.

Finally, to ensure industrial application readiness, we will expand the framework's applicability to industrial partners such as ThermoKing's products from Trane. As we prepare for commercial deployment, our focus will be on refining low-confidence anomaly detection at the edge by incorporating robust AI models. This will enhance reliability and foster trust in AI-driven maintenance scheduling, supporting the seamless transition of our research innovations into real-world applications.

6.2 Relationship with Future Research and Development

Our preliminary solution serves as an advanced sensor-analyzer framework initially designed for OBD2-based system maintenance in collaboration with our partner. As part of our broader research and development roadmap, we plan to expand its capabilities to support additional vehicle diagnostic parameters that we have found in interested commercial partners such as Trane, aligning with industry standards such as SAE J1850 and SAE J1939.

Current tools for SAE J1850, such as VPW Analyzer, facilitate bus traffic monitoring but lack remote transmission and analytics. Similarly, while libraries like J1850-VPW-Arduino-Transceiver-Library and J1850VPWCore enable communication theses still do not provide analytical frameworks like the one we are proposing here. For SAE J1939, solutions like CAN-utils, Truck Devil, and Python-CAN-J1939 support ECU interaction and diagnostic data extraction, while Open-SAE-J1939 offers a modular framework for embedded systems. However, none of these solutions incorporate advanced data analysis that we are proposing to develop a foundation in our Phase 1 work and expand on our future Phase 2 work.

Our proposed Phase I research will focus on developing an initial analytical framework capable of real-time anomaly detection and diagnostics. Phase II will build upon this foundation by integrating machine learning models for predictive maintenance, enhancing system intelligence and adaptability. This progression aligns with our long-term research vision of creating a robust, scalable, and data-driven vehicle diagnostics platform.

7 Facilities

AI POW LLC has established a robust network of research and development facilities to support the successful execution of **Phase I**, ensuring access to state-of-the-art instrumentation, computational resources, and prototyping environments. These facilities, strategically located in **Texas and California**, provide the necessary infrastructure for AI model development, real-time data acquisition, and hardware integration.

The **headquarters in Houston, TX** serves as the central administrative and operational hub. This facility is equipped with secure, high-performance networking infrastructure that enables seamless collaboration across teams. It provides access to AWS cloud computing services for large-scale AI model training, testing, and deployment. Additionally, version-controlled code repositories and data storage systems ensure that all research and development activities remain well-documented and accessible. The Bellaire location will play a key role in Phase I by overseeing project coordination, data management, and computational analysis.

To support hardware development and real-time AI integration, AI POW LLC has established a **cutting-edge research lab in Sacramento, California**. This facility is specifically designed for AI-driven **sensor integration, data acquisition, and hardware prototyping**. The lab is equipped with **custom data acquisition (DAQ) systems**, **edge computing hardware**, **high-resolution imaging systems**, and **sensor calibration tools** to facilitate rigorous testing and validation. Prototyping workstations with electronic measurement and debugging equipment allow for the development and fine-tuning of AI-powered industrial applications. This lab will be crucial in Phase I, serving as the primary site for **real-world testing and integration** of AI models with physical sensors and data acquisition systems.

Together, these three facilities provide AI POW LLC with a **comprehensive research ecosystem** that supports AI-driven innovation from concept to deployment. The integration of **cloud computing, AI model development, and hardware prototyping** ensures that Phase I research activities are executed efficiently and effectively. By leveraging these strategically located resources, AI POW LLC is well-positioned to advance cutting-edge AI technologies and deliver scalable solutions to market.

8 Consultants

Dr. Yunpeng "Jack" Zhang will serve as a consultant, leveraging his expertise in cybersecurity, artificial intelligence, and the IoT to enhance DataEdge's security, reliability, and compliance. As Director of CYBER-CARE at the University of Houston, he specializes in securing connected and automated vehicle systems. He will provide guidance on cybersecurity best practices, secure data analytics integration, and regulatory compliance while improving data integrity in IoT-enabled transit infrastructure. Additionally, he will offer insights on policy alignment to ensure DataEdge meets industry and federal standards, strengthening its foundation as an efficient predictive maintenance solution for public transit systems.

9 Potential Post Applications

The DataEdge platform presents strong commercial potential, extending beyond public transit to industries requiring reliable predictive maintenance. **A key player our team has approached is Trane (see letter of support)**, a leader in cold chain logistics and refrigerated food transportation. **Our solution has the potential to be adapted to monitor and detect anomalies in truck-mounted refrigeration units, ensuring temperature stability, reducing spoilage risks, and improving operational efficiency**. Leveraging the core components developed in this project—including the edge device with additional functional modules, the cloud-based data analytics platform, and the lightweight model optimized for edge deployment—we will extend DataEdge's capabilities to refrigeration monitoring. This adaptation will involve integrating refrigerator-specific sensors for enhanced data collection and fine-tuning the model to detect anomalies in temperature control and compressor performance, making it a valuable asset for logistics industries.

Beyond commercial applications, DataEdge aligns with Federal Government objectives for fleet modernization and operational efficiency. Agencies such as the **General Services Administration and United States Postal Service manage extensive vehicle fleets** that require cost-effective, data-driven maintenance solutions. By providing interpretable, AI-driven diagnostics, DataEdge enhances fleet readiness, reduces maintenance costs, and supports sustainability initiatives by minimizing unnecessary part replacements and energy waste. Its potential integration with federal fleet management programs and smart infrastructure initiatives positions DataEdge as a strategic tool for improving the reliability and cost-effectiveness of government-operated transportation assets.

10 Similar Offers and/or Awards

Not Applicable.

11 Human Factors

Not Applicable.

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Letter of Collaboration 1

DWIGHT LOOK
COLLEGE OF ENGINEERING

Zachry Department of Civil & Environmental Engineering

March 6, 2025

John A. Volpe National Transportation Systems Center
U.S. Department of Transportation
220 Binney Street
Cambridge, MA 02142-1093

Dear review panel,

I am writing to express my support for Dr. Alfredo Costilla Reyes's proposal, *DataEdge: Transforming Public Transit with Scalable Edge AI for Predictive Bus Maintenance.* This project aims to enhance predictive maintenance in public transit by leveraging explainable AI solutions to improve efficiency, reduce downtime, and optimize maintenance decision-making.

Current AI approaches need explainability to build trust and ensure effective adoption in transit maintenance. Without clear insights, AI-generated predictions can be difficult to interpret, limiting their practical use. DataEdge addresses this challenge by providing interpretable insights, enabling technicians to understand failure predictions and offering structured recommendations for managers and executives. By making AI-driven maintenance strategies more transparent and actionable, DataEdge fosters trust and facilitates smoother integration into transit operations.

At Texas A&M University, we are committed to advancing transportation infrastructure, and this project aligns with our efforts to integrate emerging technologies into transit operations. Our collaboration will provide expertise in transportation systems engineering, access to transit data, and support for deploying and evaluating the proposed technologies in real-world public transit environments. I will also serve as a point of contact with transportation agencies in Texas, helping to facilitate collaboration and ensure the project's successful implementation.

We see strong potential for DataEdge to improve transit maintenance practices, increase reliability, and enhance workforce readiness through AI-driven decision-making. The project's emphasis on integrating AI insights into maintenance workflows aligns with ongoing efforts to modernize transit operations and ensure sustainable, long-term improvements.

I look forward to the opportunity to collaborate on this initiative.

Sincerely,

Yunlong Zhang, Ph.D.
Peter C. Forster 61 Professor
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Letter of Collaboration 2

March 06, 2025

U.S. Department of Transportation
John A. Volpe National Transportation Systems Center
Small Business Innovation Research Program
220 Binney Street, Kendall Square
Cambridge, MA 02142-1093

Subject: Letter of Interest for the Proposal: *"DataEdge: Transforming Public Transit with Scalable Edge AI for Predictive Bus Maintenance"* (DOT Topic 25-FT1)

Dear Review Panel,

On behalf of Traf-O-Data, I am pleased to submit this letter of interest in support of the proposal titled **"DataEdge: Transforming Public Transit with Scalable Edge AI for Predictive Bus Maintenance"**, led by **Dr. Alfredo Costilla Reyes** and his team.

As a leader in providing safe, efficient, and reliable public transportation across the State of Florida, Traf-O-Data recognizes the importance of adopting cutting-edge technologies to optimize operations and enhance passenger experiences. This proposal's focus on applying **artificial intelligence (AI) on edge devices** for predictive maintenance aligns with our mission to improve fleet reliability, reduce operational costs, and modernize our transit infrastructure.

We believe this project has significant potential to address critical maintenance challenges, including the monitoring of **on-bus HVAC systems**, which are essential for passenger comfort year-round, particularly in extreme climate conditions. Additionally, this initiative offers predictive maintenance capabilities for other essential **bus-specific components**, including **engine cooling systems, battery voltage and current levels, brake pressure sensors, and temperature monitoring systems**. Proactively managing these systems will help prevent unexpected breakdowns, improve operational efficiency, and extend the lifespan of the bus fleet.

Traf-O-Data is enthusiastic about the opportunity to collaborate with **Dr. Costilla Reyes** and his team. We are ready to support this project by facilitating **data collection** and offering **operational feedback** to ensure the technology effectively addresses the practical needs and challenges faced by transit agencies.

We look forward to supporting this initiative and believe it has the potential to bring meaningful improvements to public transportation systems nationwide. Please feel free to contact me if you need any further information.

Sincerely,

Chunyu Lu 03/06/2025

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Letter of Collaboration 3

TRANE
TECHNOLOGIES

March 5, 2025

U.S. Department of Transportation
Small Business Innovation Research Program

Subject: Letter of Support – DataEdge: Transforming Public Transit with Scalable Edge AI for Predictive Bus Maintenance

Dear Review Panel of DOT Topic 25-FT1,

This letter is to express Trane US Inc.'s (Trane's) interest in Data Edge's proposal to the DOT, titled "DataEdge: Transforming Public Transit with Scalable Edge AI for Predictive Bus Maintenance". Trane U.S. Inc. (Trane) is a subsidiary of TUI Holdings Inc. and a global climate innovator.

It was a pleasure meeting with Dr. Alfredo Costilla Reyes to learn more about the DataEdge project and its innovative approach to predictive maintenance. As a leader in HVAC and cold chain logistics, Trane recognizes the importance of reliable and data-driven maintenance solutions to optimize efficiency and minimize downtime.

While DataEdge is designed with public transit in mind, our discussions highlighted its broader applications in cold chain logistics and refrigerated transport systems. The ability to leverage edge AI technology to monitor critical components, detect anomalies, and provide actionable insights has the potential to improve system reliability across multiple industries. We see promise in the DataEdge platform's ability to enhance predictive maintenance for truck-mounted refrigeration units, ensuring temperature stability, reducing spoilage risks, and improving operational efficiency.

Should this project receive funding, Trane looks forward to continuing conversations with Dr. Costilla Reyes and his team to explore potential collaborations. We believe that this technology could play a transformative role in our industry, where it can contribute to smarter, more resilient fleet management solutions.

Sincerely,

Kenneth A. Schoeneck, Jr.

Kenneth A. Schoeneck, Jr.
VP, Engineering & Technology