A Data-Driven Approach to Predict Fuel Rail Pressure Anomalies in Internal Combustion Engines

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***Abstract*—Maintaining Optimal fuel rail pressure (FRP) control is essential in common rail diesel engines. It ensures efficient combustion, good fuel economy, and low emissions. Conventional Engine Control Unit (ECU) threshold-based detection methods often fail to identify subtle, early deterioration in FRP, resulting in delayed fault diagnosis and increased operational impact for fleet operators. This paper proposes a multi-parametric data-driven approach for the real-time detection of FRP anomalies under dynamic, real-world driving conditions. Real-time, high-resolution sensor data from the On-Board Diagnostics (OBD) interface is used to train predictive machine learning models. A Gaussian Mixture Model (GMM)-based outlier detection framework is developed and rigorously benchmarked against a baseline Linear Regression (LR) model trained on healthy data. GMM is found to be the most effective method for identifying common rail pressure anomalies. The approach has been validated on a fleet of 63 heavy-duty diesel vehicles with engine displacements of 12000–15000 cc and power outputs of 400–600 hp. Diagnostic Trouble Codes (DTCs) from the ECU have been used as ground truth for evaluating anomaly detection performance. The proposed GMM-based model achieves an average accuracy of 80% in forecasting FRP issues 3–10 days in advance, representing a 45% improvement in accuracy over LR. The proposed predictive framework enables enables proactive maintenance of common rail fuel systems.**

***Index Terms*—FRP, RPM, GMM, OBD, Predictive Maintenance**

I. Introduction

High-pressure common rail (CR) fuel systems have fundamentally transformed fuel delivery system in diesel and compressed natural gas (CNG) engines since the 1990s. CR systems decouple pressure generation from the injection event. These CR systems maintains a fuel at consistently high pressure typically ranging from 90 to over 2000 bar. This stable precise pressure control enables superior fuel atomization and results into measurable gains such as, more complete combustion, fuel efficiency, reduced exhaust emissions, enhanced overall engine performance and compliance with stringent emissions regulations (e.g., Euro-VI, BS-VI) [1]. The shift from mechanically governed systems to this electronically controlled technology represents a key paradigm change in engine design [2] [3]. Unlike older systems where fuel pressure varied directly with engine speed, the CR acts as a stable pressure accumulator, supplying fuel at constant high pressure independent of engine load. This stability is crucial for maintaining uniform injection characteristics and combustion quality across diverse operating condition such as, from idle to full load and under varying ambient temperatures and altitudes. Despite this fundamental technological advantage, ensuring the optimal maintenance of FRP stability during extended real-world operation remains difficult. Commercial heavy-duty vehicles frequently encounter complex duty cycles, component degradation due to long-term wear (e.g., pump and injector wear), and variability stemming from fuel quality or sensor faults. Pressure deviations arising from injector leakage, high-pressure pump degradation, pressure relief valve (PRV) malfunction, or sensor inaccuracies can severely impair combustion efficiency, increase pollutant formation, and ultimately trigger costly mechanical failures [1] [4]. Traditional threshold-based fault detection algorithms embedded within Engine Control Units (ECUs) are inherently reactive. These systems monitor FRP against static limits and often fail to detect gradual or subtle abnormalities that indicate early-stage component deterioration. This limitation frequently delays maintenance intervention which results into increased vehicle downtime and the total cost of ownership for fleet operators. Therefore, there is a critical need for proactive, data-driven methodologies that can continuously monitor FRP dynamics and predict anomalies at an early stage.

In this paper, we propose a multi-parametric data-driven approach for the real-time prediction of FRP anomalies. We leverage high-resolution sensor data including FRP and Engine Speed (RPM) acquired through the vehicle's On-Board Diagnostics (OBD) system. This data is utilized to train and validate a Gaussian Mixture Model (GMM)-based outlier detection framework. This data is processed in the cloud using a proposed algorithm to effectively capture early deviations from normal FRP behavior and predicts anomalies in fuel rail pressure with high accuracy. The proposed method is validated against Diagnostic Trouble Codes (DTCs) generated by the ECU, demonstrating its potential for reliable predictive maintenance and enhanced fuel system control strategies. The processing can also be performed directly on the installed OBD edge device if sufficient computational resources are available. Due to the nature of the algorithm, it can be operate with minimal computational requirements.

The remainder of this paper is organized as follows: Section 2 reviews related work on fuel system diagnostics and predic-

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tive maintenance methodologies. Section 3 describes the data acquisition infrastructure and preprocessing pipeline. Section 4 presents the GMM-based anomaly detection framework and the comparative baseline models. Section 5 details the experimental results and performance evaluation, while Section 6 concludes the paper and outlines future scope.

II. Related Work

A. Fuel System Diagnostic Approaches

Health monitoring for CR fuel systems has primarily been advanced through two complementary methodological frameworks: model-based and data-driven diagnostics. Model-Based Methods utilize a physical understanding of the system dynamics to detect anomalies [5], [6]. These approaches often employ state estimators, such as Kalman filters [6], or 1D fluid dynamics models to predict the expected rail pressure [5] . While effective, these methods require extensive parameter tuning for each engine variant and demand significant computational resources, limiting their scalability for embedded deployment. Crucially, they often fail to capture the subtle, long-term degradation patterns prevalent in operational fleets. Traditional Data-Driven Methods offer an alternative by identifying anomalies directly from sensor data without requiring explicit physical modeling. Existing literature has explored techniques such as polynomial regression profile monitoring [7] and basic machine learning classifiers. However, these methods struggle with robustness in dynamic environments. They are typically vulnerable to sensor noise, highly susceptible to transient operational effects (like rapid acceleration), and their validation is often confined to simulated or heavily preprocessed data, limiting their predictive accuracy in real-world, high-variability scenarios. These methods lacks to provide early, robust fault prediction across diverse driving cycles without high computational cost or restrictive system-specific calibration.

B. Low Fuel Rail Pressure Failures

Low FRP conditions are the most common source of system impairment, leading to poor atomization, reduced power, and increased smoke emissions. The principal root causes of low FRP, as identified in the literature, are component degradation, wear, and leakage. Pump Degradation and Wear is a gradual failure mode characterized by a drop in volumetric efficiency resulting from internal component wear, such as plunger or seal degradation ([8], [9]). Studies indicate that contaminated or low-lubricity fuels can accelerate this wear, leading to progressive pressure deficits over the engine's lifespan [10]. Leakage Failures occurring in injectors, pressure regulators, or high-pressure lines can result in uncontrolled fuel loss from the rail. This causes a systemic FRP deficit and disrupts combustion synchronization.

C. High Fuel Rail Pressure Failures

Excessive rail pressure primarily poses safety and reliability risks. The Pressure Relief Valve (PRV) is mandated as the critical protective mechanism, designed to vent excess fuel

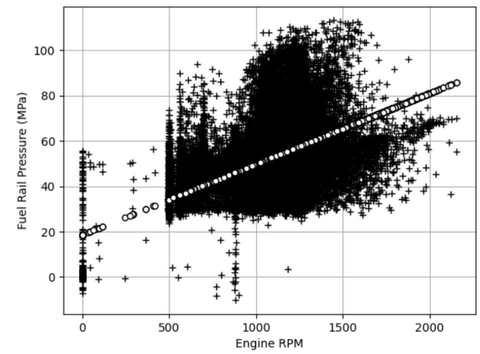

Fig. 1: Scatter plot showing FRP vs. Engine RPM data collected from 24 healthy vehicles ($N > 430K$). The fitted regression line demonstrates a positive correlation ($R^2 = 0.43$). The data clustering shows the approximate Gaussian distribution of FRP around the trend line ($\sigma \approx \pm 9.6$ MPa), which justifies the use of GMMs.

when pressure exceeds regulatory or design pressure limits [11], [12]. Failures within the pressure control loop such as PRV stiction or malfunction, can lead to uncontrolled high FRP. This results into over-fueling, poor fuel economy, and reduced engine performance [13].

III. System Overview and Methodology

The proposed methodology detects and predicts anomalies in FRP under real-world operating conditions by leveraging real-time sensor data and a GMM based outlier detection framework.

A. Data Acquisition

Vehicle sensor data is collected in real time through the OBD interface using a proprietary telematics device (Intangles Lab's product) [14]. The key parameters include FRP, Engine RPM, Engine Load, and Throttle Position. Data is collected and sampled at 8-second intervals using a proprietary hardware device and transmitted to the cloud for further processing. Under typical engine operation, FRP naturally varies significantly with engine RPM. Lower demand, such as during idle conditions (lower RPM, load and throttle), corresponds to reduced FRP, while high load requires elevated pressure to ensure adequate fuel delivery for combustion. To minimize this inherent operational variability during the analysis phase, we implement a data filtering step. FRP values are filtered and analyzed only when the engine operates within the peak torque RPM range (as specified by the manufacturer). Analysis is further restricted to periods indicating sufficient power demand (at least 30% engine load and 10% throttle position).

B. Predictor Selection and Correlation Analysis

To identify the most relevant predictors for FRP anomaly detection, an empirical analysis was performed to examine relationships between FRP and three engine parameters: Engine

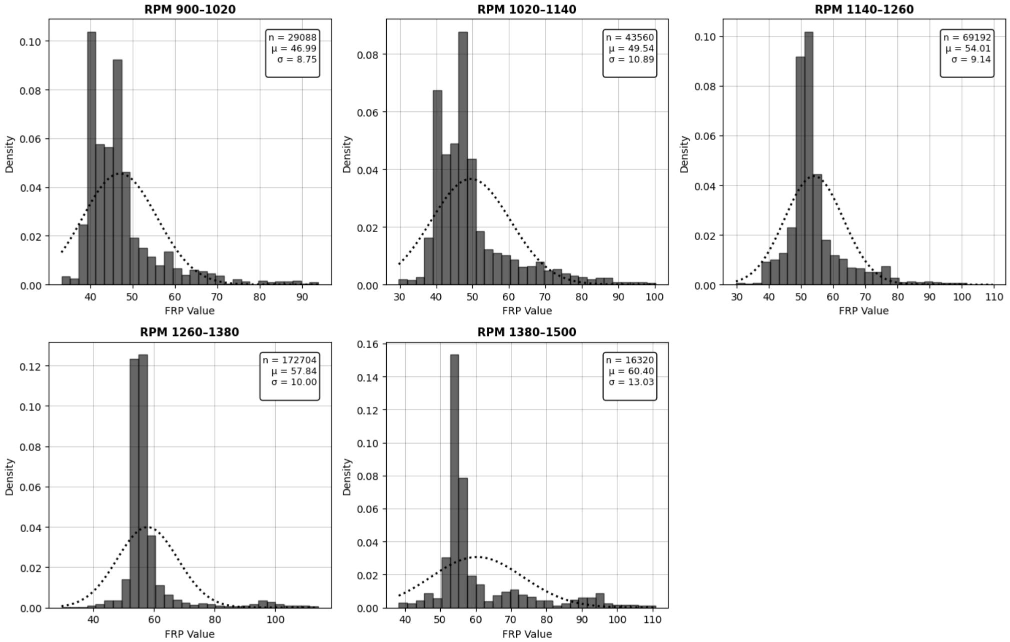

Fig. 2: Normalized FRP histograms across five RPM bins. The clear multimodality and asymmetric distributions indicate that the FRP behavior cannot be modeled by a single normal distribution, necessitating the use of a Gaussian Mixture Model (GMM).

RPM, Engine Load, and Accelerator Pedal Position (Throttle). Among these, Engine RPM exhibited a strong and consistent positive association with FRP across diverse driving conditions including urban, highway, and mixed-cycle operations. This correlation is illustrated by the scatter plot in Figure 1, which is derived from over 430,000 measurements collected from 24 healthy vehicles. This fitted regression line with a positive slope indicates that FRP increases with RPM. Furthermore, the FRP measurements follow an approximately Gaussian distribution around this central trend, reflecting natural variability in fuel demand with a standard deviation of roughly ± 9.6 MPa. This consistent distributional characteristic provides the theoretical foundation for applying the GMM. The adoption of a GMM for FRP modeling is supported by multiple quantitative indicators. Figure 2 illustrates the empirical FRP distributions across five RPM bins (900–1500 RPM). These distributions exhibit characteristics such as positive skewness (1.7–2.1) and excess kurtosis (2.6–11.65), which indicates right-skewed and heavy-tailed behavior. This multimodal nature necessitates the use of a mixture-based statistical model, as a single normal distribution is insufficient to represent the data adequately. In contrast, Engine Load and Accelerator Pedal Position were found to have weak or inconsistent relationships and were thus deemed unsuitable as primary predictors. Therefore, Engine RPM was selected as the key feature for FRP modeling and anomaly detection.

C. Proposed Algorithm

The proposed anomaly detection approach is based on a Gaussian Mixture Model (GMM) [15] fitted to healthy vehicle data, which continuously monitors fuel rail pressure and classifies vehicle operational states. The overall process of model building is illustrated in Fig. 3, while the steps for anomaly prediction during inference time is shown in Fig. 4. The GMM was trained exclusively on two months of data collected from 10 healthy vehicles. This training volume was selected to capture sufficient operational variability and establish a robust baseline for normal behavior. Data acquisition was performed at an 8-second sampling rate. This choice considered two key factors: (1) cloud storage constraints inherent to the IoT deployment architecture, and (2) the characteristic gradual development of FRP anomalies. Since these anomalies develop over several seconds rather than instantaneously, the 8-second interval is sufficient for reliable detection while maintaining manageable data storage. The algorithm comprises the following steps:

- **Baseline Characterization:** The Fuel Rail Pressure (FRP) data is first divided into five distinct RPM bins to capture variation due to different engine operating conditions.For each bin, a Gaussian Mixture Model (GMM) is fitted to characterize the normal FRP behavior. The GMM models the FRP distribution as a sum of K Gaussian components, each with its own mean μ_j and variance σ_j^2:

$$p(\text{FRP}) = \sum_{j=1}^{K} \mathcal{N}(\text{FRP} \mid \mu_j, \sigma_j^2)$$

We utilized a fixed $K = 3$ GMM uniformly across all RPM bins. The optimal number of components (K)

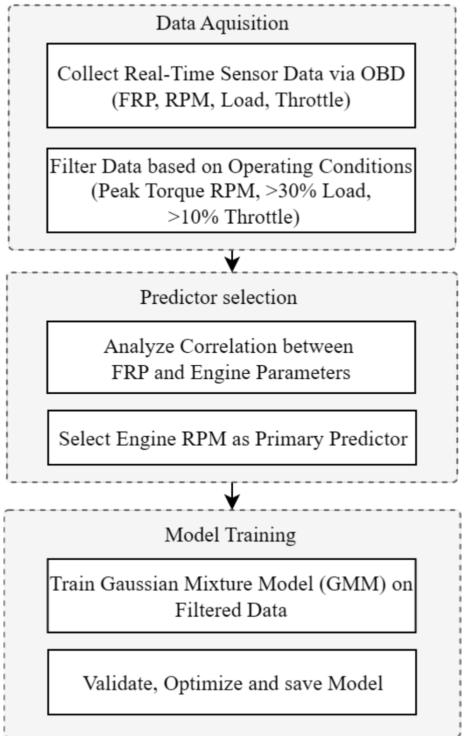

Fig. 3: Block Diagram for proposed Model Building

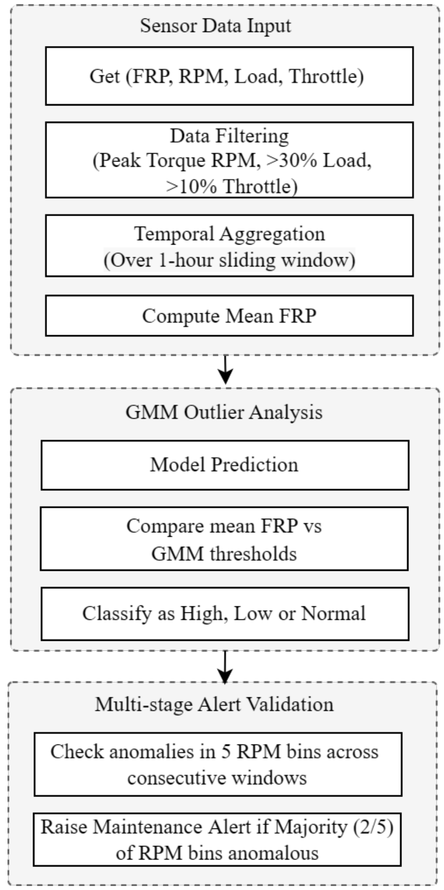

Fig. 4: Pipeline for anomaly prediction during inference time

was determined using the Bayesian Information Criterion (BIC), a metric that balances model fit against complexity, by testing values for $K \in \{1, 2, 3, 4, 5\}$. As detailed in Figure 5, the BIC generally minimized near $K = 3$ across most bins. $K = 3$ was adopted universally to ensure consistency and maintain a uniform physical interpretation of the modeled behavior across the engine's operating range. The derived parameters (μ_j and σ_j) serve as the statistical baseline to detect deviations representing anomalies in FRP behavior.

- **Temporal Aggregation:** During inference, FRP measurements are aggregated using a 1-hour sliding window with a stride of one sample to compute the mean FRP value. This aggregation helps reduce noise and transient effects. Specifically, 450 samples (each taken at 8-second intervals) are collected to form a 1-hour context window, and the mean FRP is calculated as

$$\bar{x}_{\text{FRP}} = \frac{1}{N} \sum_{i=1}^{N} frp_i \tag{1}$$

  where:
  - $\bar{x}_{\text{FRP}}$ is the mean FRP over the observation window,
  - frp_i is the i^{th} individual FRP measurement sample,
  - $N = 450$ is the total number of samples in the observation window,
  - Samples are collected at 8-second intervals, so $N \times 8$ seconds $= 1$ hour.
- **Outlier Detection:** Anomaly detection is performed by comparing the aggregated FRP value $\bar{x}_{\text{FRP}}$ to empirical thresholds based on the fitted GMM parameters in the respective RPM bin. For each Gaussian component j:
  - High-FRP Outlier: $\bar{x}_{\text{FRP}} > \mu_j + 3\sigma_j$
  - Low-FRP Outlier: $\bar{x}_{\text{FRP}} < \mu_j - 2\sigma_j$
  - Optimal Range: $\mu_j - 2\sigma_j \leq \bar{x}_{\text{FRP}} \leq \mu_j + 3\sigma_j$

  The asymmetric 3σ (upper) and 2σ (lower) thresholds are established based on both empirical validation and domain-specific operational considerations. The tighter lower threshold (2σ) reflects the critical nature of low FRP conditions such as, insufficient fuel pressure immediately leads to poor fuel atomization, incomplete combustion, and potential vehicle stalling during operation. In contrast, the relaxed upper threshold (3σ) accounts for the inherent protection provided by the PRV, which regulates excessive pressures under normal circumstances. High FRP conditions become critical only when pressures exceed the PRV's design limits, indicating potential PRV failure or severe system malfunction. This asymmetric threshold design prioritizes early detection of low-pressure anomalies while minimizing false alarms for transient high-pressure events that are naturally regulated by the PRV. As shown in Fig. 2, FRP distributions exhibit consistent positive skewness across all RPM bins, with a longer tail toward high pressures. Additionally,

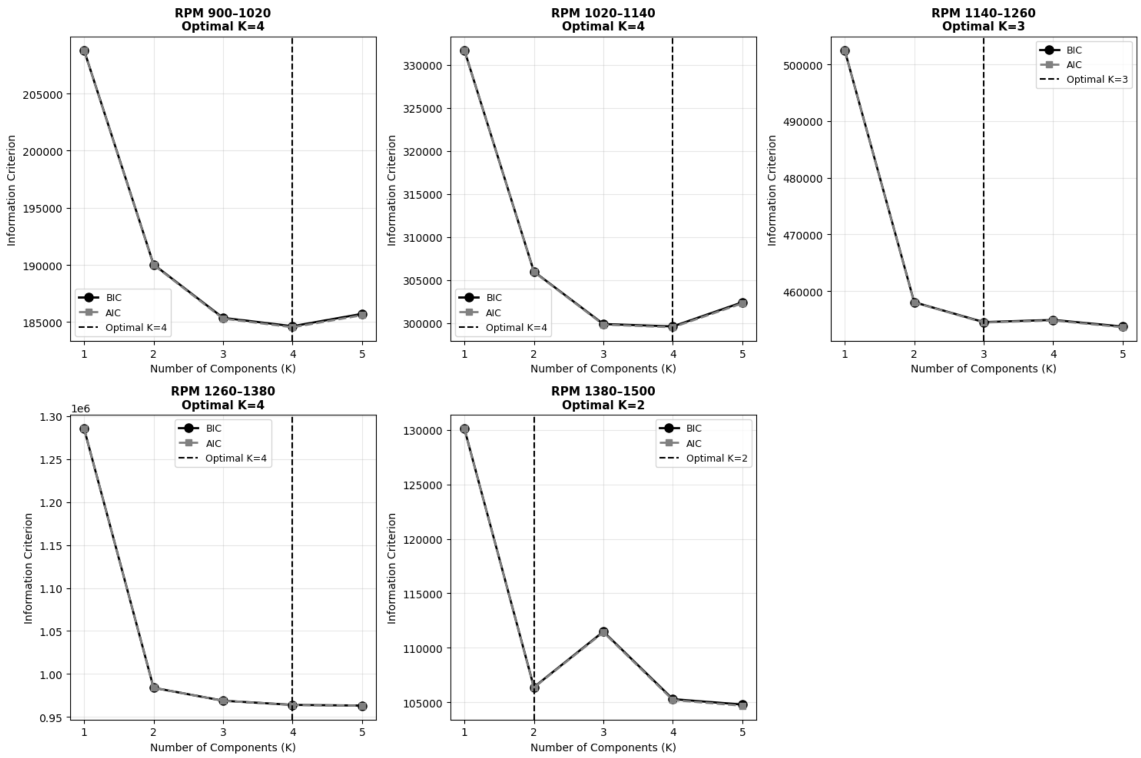

Fig. 5: BIC and AIC values as a function of GMM components (K) for each RPM bin. The minimum BIC (dashed line) guides the selection of the optimal K, which led to the uniform adoption of $K = 3$ for all bins.

these results were validated against ground truth (low & high FRP cases) to determine suitable standard deviation multipliers.

- **Multi-Stage Alert Validation:** To ensure robust anomaly prediction and reduce false positives, a multi-stage validation process is employed before issuing maintenance alerts. The classification is performed independently across five equally spaced RPM bins. An alert is triggered only when at least two out of the five RPM bins exhibit anomalous behavior (either high-FRP or low-FRP outliers), and this condition persists across five consecutive observation windows. The alert type (high-FRP or low-FRP) is determined by the majority classification among the anomalous bins.

IV. Results and Discussion

Table I presents the lead time between predictive alerts and DTC occurrence for both high and low FRP scenarios for GMM as the model. The results and predictions of the proposed algorithm are validated against a LR model trained on normal operating data, where all system states are healthy. This establishes the baseline relationship between input parameters and FRP output. Data points are classified as outliers when the residual magnitude (positive or negative) exceeds the expected FRP value beyond a predefined threshold. The performance of each model is evaluated using FRP-associated DTCs provided by the ECU, demonstrating its effectiveness in real-world applications. Validation was performed using vehicles exhibiting specific DTCs: 521031-18, 9D001, and 157-17 corresponding to low FRP events, and 157-16 and 521031-16 corresponding to high FRP events. These DTCs were required to be consistently preceded by predictive alerts labeled “Fuel Rail Pressure Low” or “Fuel Rail Pressure High.” The former was triggered following consecutive occurrences of low FRP values, while the latter was generated after consecutive high FRP instances, both identified within the relevant RPM bins by the GMM. The vehicles with no low-FRP and high-FRP associated DTCs are considered for healthy cohort analysis. All such instances were collected over a period spanning from December 2024 to September 2025. Two months of data from 10 healthy vehicles were utilized to train the GMM and it’s baseline LR. The study focused on heavy-duty vehicles with engine displacement ranging from 12000 to 15000 cc and power output between 400 and 600 hp.

A. Gaussian Mixture Model Validation

The proposed GMM-based anomaly prediction algorithm has been evaluated across three distinct FRP scenarios: Low FRP, High FRP, and Optimal FRP conditions. Performance was assessed using vehicles with confirmed FRP-related DTCs, enabling validation against ground truth fault conditions.

1) Low FRP Prediction: For the Low FRP scenario, 20 vehicles exhibiting low FRP-associated fault codes were evaluated. The model successfully identified FRP anomalies at least

TABLE I: GMM based predicted Alerts validation with Diagnostic Trouble Codes (DTCs)

Predicted FRP Alert Time	**DTC Code + Description**	**DTC Time**
Oct 13th 2025 1:10 am	157-17 - Fuel Rail Pressure: Data Valid But Below Normal Operating Range - Least Severe Level 521031-18 - Fuel Pressure Deviation Too Low: Data Valid But Below Normal Operating Range - Moderately Severe Level	Oct 15th 2025, 6:09:29 am
May 30th 2025 18:05:15 am	157-17 - Fuel Rail Pressure: Data Valid But Below Normal Operating Range - Least Severe Level 157-10 - Fuel Rail Pressure: Mechanical Or Electrical Fault	Jun 5th 2025, 1:11:57 am / 1:47:24 am
May 31st 2025 0:49:00	157-17 - Fuel Rail Pressure: Data Valid But Below Normal Operating Range - Least Severe Level 9D0011 - Engine Fuel 1 Injector Metering Rail 1 Pressure: Data Valid But Below Normal Operating Range - Least Severe Level	Jun 11th 2025, 2:20:17 pm
Aug 24th 2025 21:25:00	157-17 - Fuel Rail Pressure: Data Valid But Below Normal Operating Range - Least Severe Level	Aug 26th 2025, 5:18:03 am
Aug 16th 2025 9:22:03 am	157-17 - Fuel Rail Pressure: Data Valid But Below Normal Operating Range - Least Severe Level	Aug 17th 2025, 5:41:46 pm
Jul 26th 2025 4:45:00 am	157-17 - Fuel Rail Pressure: Data Valid But Below Normal Operating Range - Least Severe Level 9D0011 - Engine Fuel 1 Injector Metering Rail 1 Pressure: Data Valid But Below Normal Operating Range - Least Severe Level	Aug 1st 2025, 12:41:46 am
Aug 24th 2025 0:11:00 am	157-17 - Fuel Rail Pressure: Data Valid But Below Normal Operating Range - Least Severe Level	Aug 28th 2025, 5:48:42 am
Dec 8th 2025, 4:00:02 am	157-16 - Fuel Rail Pressure: Data Valid But Above Normal Operating Range - Moderately Severe Level	Dec 31st 2024, 5:59:05 pm
Dec 2nd 2025, 21:55:00 pm	521031-16 - Fuel Pressure Deviation Too Low: Data Valid But Above Normal Operating Range - Moderately Severe Level	Dec 5th 2024, 1:34:51 pm
Dec 4th 2025, 2:53:00 am	521031-16 - Fuel Pressure Deviation Too Low: Data Valid But Above Normal Operating Range - Moderately Severe Level	Dec 9th 2024, 8:02:00 am

one day in advance in 17 out of 20 vehicles (85% accuracy). In the remaining 3 vehicles (15%), the model failed to raise alerts due to either: (i) insufficient outlier bins, where the 2/5 bin criterion was not satisfied, or (ii) the anomaly not persisting across 5 consecutive observation windows. These missed predictions highlight the trade-off between sensitivity and specificity in the alert threshold calibration, suggesting that while the conservative criteria reduce false alarms, they may occasionally miss intermittent or localized anomalies.

2) High FRP Prediction: In the High FRP scenario, 12 vehicles with high FRP-related issues were evaluated. The model successfully flagged 9 vehicles (75% accuracy) as exhibiting high FRP outlier conditions. 3 vehicles (25%) were not detected, indicating potential limitations in capturing certain high FRP anomaly patterns.

3) Optimal FRP Validation: To assess the false positive rate, 31 instances of vehicles operating under optimal FRP conditions were evaluated. The model correctly identified 24 out of 31 instances (77.4% specificity) as normal, demonstrating strong performance in avoiding false alarms. However, in 7/31 cases (22.5%), the model incorrectly flagged low FRP instances as anomalies.

B. Linear Regression model for baseline comparison with GMM

Linear regression is a statistical modeling technique that establishes a linear relationship between one or more independent variables (predictors) and a dependent variable (response) [7]. In the context of FRP anomaly detection, linear regression serves as a baseline model to capture the expected relationship between Engine RPM and FRP under normal operating conditions. Using residuals from the training data, the 5th and 98th percentiles were computed for each RPM bin to establish lower and upper bounds for normal FRP behavior. For each test window of 450 samples, RPM bins were classified based on mean residual values- bins with mean residuals below the 5th percentile were labeled as Low FRP, those above the 98th percentile as High FRP, and the remaining bins as Normal. Similar, to GMM performance validation, it has been performed on Low FRP, High FRP, and Optimal FRP conditions. For low FRP, LR successfully identified FRP anomalies in 11/20 vehicles (55% accuracy). In the remaining 9 vehicles (45%). On high FRP it identified anomalies on 8/12 (67%) cases and missed raising the alert in 4/12 (33%) cases. On the optimal FRP, the model correctly identified 3/31 instances (9.67% specificity) as normal, and the remaining 28/31 (90.32%) are being tagged as anomalies.

As observed, specificity is quite low in this case. Linear Regression assumes a simple linear relationship between RPM and FRP, but the actual relationship may be more complex. A simple linear model can't capture these nuances, causing it to flag legitimate variations as anomalies. GMM based approach provides a probabilistic density estimate of the data distribution and exhibits the capability to model multiple

TABLE II: Performance validation of GMM and LR models using vehicle counts across FRP scenarios.

FRP-type	Methods	# Test Vehicles	# Vehicles with Alerts	# Vehicles without Alerts
Low FRP	GMM	20	17	3
	LR	20	11	9
High FRP	GMM	12	9	3
	LR	12	8	4
Optimal FRP	GMM	31	7	24
	LR	31	28	3

TABLE III: Performance metrics of GMM and LR models across different FRP conditions

Methods	Specificity	Sensitivity	Precision	F1-Score	Accuracy
GMM	77.4%	81.25%	79%	80.62%	80%
LR	10%	59.37%	40.42%	48%	35%

engine operations naturally through its mixture components. Unsupervised methods such as, Isolation Forest use distance-based approaches without considering the underlying distribution, providing anomaly scores rather than probabilities. This fails to capture multiple operating regimes. Similarly, the reconstruction error in autoencoders is not a true probability, and the black-box nature of the model does not provide transparency on what normal behavior looks like.

Table II summarizes the performance metrics for GMM across all three FRP scenarios. The models were further evaluated using standard performance metrics, including sensitivity (recall), specificity, and F1-score. The details of which can be seen in Table III. Overall GMM demonstrates superior performance compared to the baseline model across all the situations of High, Low and Normal FRP.

V. Conclusion

In this paper, we compared the predictive capabilities of the proposed approach with those of linear regression models for FRP anomaly detection. The proposed approach consistently demonstrated superior performance, delivering early and reliable alerts with a lead time of 3–10 days. Validation against engine control unit (ECU) Diagnostic Trouble Codes (DTCs) confirmed its efficacy, achieving a sensitivity of 85% for critical low-FRP events and 75% for high-FRP detection. These results strongly validate the practicality of unsupervised normal-behavior modeling for early fault detection in heavy-duty vehicles. Furthermore, the multi-stage alert validation mechanism, employing multiple RPM bins across consecutive windows effectively reduced false positives, enhancing the reliability of real-time monitoring. For fleet operators, FRP issues lead to decreased fuel economy and reduced mileage; our methodology helps mitigate these challenges. Current limitations include the fully data-driven nature of all decisions, including thresholds, which may not generalize across all OEMs. OEM-specific thresholds could further strengthen the approach and improve results. As future work, we plan to compare this unsupervised method with supervised alternatives using both healthy and unhealthy labels as ground truth.

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