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

Harleen Kaur Bagga, Mukund B. Nagare, Bhushan D. Patil, Hariharan Ravishankar, Vikram Melapudi, Abhijit Patil
Technology and Innovation Group,
Intangles Lab Pvt Ltd, Pune, India
{harleen.kaur, mukund.nagare, bhushan.patil, hariharan.ravishankar, vikram.melapudi, abhijit}@intangles.com

***Abstract*—Maintaining optimal fuel rail pressure (FRP) in common rail diesel engines is critical for ensuring efficient combustion, fuel economy, and emission compliance. Deviations from the ideal pressure range can lead to poor atomization, incomplete combustion, increased emissions, and reduced engine performance. Conventional fault detection strategies rely primarily on threshold-based monitoring in the engine control unit (ECU). These approaches often fail to capture subtle deterioration in rail pressure characteristics over time, resulting in late detection of common rail issues. In this paper, a multi-parametric data-driven approach is proposed for predicting anomalies in fuel rail pressure under real-world driving conditions. Real-time, high resolution sensor data obtained via the On-Board Diagnostics (OBD) interface is used to build predictive machine learning models. A Gaussian Mixture Model (GMM) based outlier detection framework is introduced and systematically benchmarked against other common ML models like linear regression (LR) modelled on healthy data for outlier identification. Among the methods evaluated, GMM proved most suitable for predicting anomalies associated with common rail fuel pressure. The performance of the proposed methodology has been validated on a fleet of 63 heavy-duty diesel vehicles with engine displacements ranging between 12,000–15,000 cubic centimeters and power outputs in the 400-600 hp range. Diagnostic Trouble Codes (DTCs) generated by the ECU were used as ground truth to assess anomaly detection accuracy. Results demonstrate that the GMM-based approach outperforms conventional machine learning classifiers in capturing early deviations from normal FRP patterns. The proposed predictive models achieve an average accuracy of 80% in forecasting FRP issues 3-10 days ahead of occurrence, outperforming the linear regression baseline method by 45%. Overall system performance indicates that the proposed framework enables predictive maintenance of common rail fuel systems, effectively reducing maintenance costs, preventing mileage loss, and minimizing operational downtime.**

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

I. Introduction

Since the 1990s, high-pressure fuel rail systems have fundamentally transformed fuel delivery system in diesel and compressed natural gas (CNG) engines, supplanting traditional mechanical injection systems and carburetors. These common rail systems maintain fuel at consistently high pressures often ranging from 90 to over 2000 bar which enables precise control of injection timing and enhancing fuel atomization [16]. Improved atomization directly translates to more complete combustion, yielding measurable gains in fuel efficiency, reduced exhaust emissions, and enhanced overall engine performance [16]. The transition from mechanically governed injection and carburetion to electronically controlled high-pressure common rail technology represents a paradigm shift in internal combustion engine design. This evolution has been driven primarily by increasingly stringent emissions regulations (e.g., Euro-VI, BS-VI) [17] [18] and the growing demand for fuel economy improvements in commercial vehicle operations. Unlike older systems where fuel pressure varied directly with engine speed, the common rail functions as a stable pressure accumulator, supplying fuel at constant pressure independent of engine load or speed. This stability is essential 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 these technological advances, maintaining optimal fuel rail pressure (FRP) under real-world operating conditions remains a challenge. Commercial vehicles encounter complex duty cycles, component degradation due to wear, fuel quality variations, and sensor faults over long service intervals. Pressure deviations arising from injector leakage, high-pressure pump degradation, pressure relief valve (PRV) malfunction, or sensor inaccuracies can significantly impair combustion efficiency, increase pollutant formation, reduce engine responsiveness [20] [21], and ultimately trigger costly mechanical failures.

Traditional threshold-based fault detection algorithms embedded within engine control units (ECUs) are inherently reactive and often fail to detect gradual abnormalities in FRP. This limitation frequently delays maintenance, increasing downtime and raising total cost of ownership for fleet operators. Therefore, there is a clear need for proactive, data-driven methodologies that can continuously monitor FRP dynamics, detect anomalies at an early stage. Such methods can safeguard engine performance, ensure regulatory compliance, and optimize maintenance schedules.

In this paper, we propose a novel approach that utilizes real-time sensor data, such as fuel-rail pressure, engine speed (RPM), acquired through the vehicle's On-Board Diagnostics (OBD) system. This data is processed in the cloud using a proposed algorithm to predict anomalies in fuel rail pressure with high accuracy. By employing a Gaussian Mixture Model

Identify applicable funding agency here. If none, delete this.

(GMM) based outlier detection framework, the approach captures early deviations from normal FRP behavior more effectively than conventional classifiers. 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 proposed method is validated against diagnostic trouble codes (DTCs) generated by the engine control unit (ECU), demonstrating its potential for predictive maintenance and enhanced control strategies in fuel system.

The remainder of this paper is organized as follows: Section 2 reviews related work on fuel system diagnostics and predictive maintenance methodologies. Section 3 describes the data acquisition infrastructure and preprocessing pipeline. Section 4 presents an overview of the GMM-based anomaly detection framework, along with other anomaly prediction classifiers such as linear regression (used as an outlier detection framework),

II. Background and Motivation

A. Common Rail Fuel System Technology

Common Rail Direct Injection (CRDI) technology has revolutionized diesel engine performance which provides precise control over over injection pressure, timing, quantity and duration [1]. Unlike conventional injection systems where pressure generation is mechanically coupled to injection events, CRDI systems decouple these functions where a high-pressure pump maintains rail pressure independently, while electronically-controlled injectors meter out the exact fuel required for each cycle [2]. Modern CRDI systems operate at pressures ranging from 20 MPa to over 250 MPa ([3], [4]), enabling multiple injection events per combustion cycle and improved fuel atomization. This pressure flexibility allows efficient combustion, compliance with stringent emissions regulations while maintaining fuel efficiency.

B. Low Fuel Rail Pressure as an Issue

Low FRP conditions can lead to poor atomization and incomplete combustion, resulting in loss of power, increased smoke emissions, and potential component wear. Several researchers have identified the root causes of low FRP in the literature, such as pump wear and degradation, contaminated or low-lubricity fuels, and injector leakage or valve malfunctions, and have examined their impacts on system components. Pump Degradation & Wear is a a gradual failure mode where volumetric efficiency drops due to plunger wear, seal degradation, or internal leakage ([5], [6]). [7] demonstrated that, the contaminated or low-lubricity fuels can accelerate the pump wear and cause pressure reductions of up to 15-30% over the engine lifetime. Other issues such as injector leakage or valve malfunctions lead to inconsistent pressure delivery and disrupt combustion synchronization.

C. High Fuel Rail Pressure as an Issue

Excessive rail pressure poses significant safety and reliability risks, with the pressure relief valve (PRV) serving as the primary protection mechanism. PRV, a critical safety component, is designed to prevent rail over pressurization by venting excess fuel when pressure exceeds design limits (typically 180-220 MPa) [8], [9]. PRV failures can lead to high FRP, which can lead to the engine running too rich, causing poor fuel economy and reduced engine performance [12].

D. Limitations of Existing Approaches

Current FRP monitoring strategies suffer from complementary weaknesses. Model-based methods [13], [14] utilize physical system models such as 1D fluid dynamics or Kalman filter state estimators to predict expected rail pressure and flag deviations as faults. While theoretically sound, these approaches require extensive parameter tuning for each engine variant, demand significant computational resources unsuitable for embedded automotive systems, and may fail to capture long-term degradation patterns or real-world operational variability. Data-driven alternatives [15], including polynomial regression profile monitoring and machine learning classifiers, eliminate the need for explicit physical modeling but face different challenges- validation on simulated rather than production data, vulnerability to sensor noise and transient effects, and poor performance under rapidly changing operating conditions (e.g., temporary acceleration, high-load events). Neither paradigm enables early, robust fault detection across diverse driving scenarios without restrictive calibration effort or computational cost.

We overcome these limitations through empirical statistical modeling through GMMs that characterize normal FRP distributions learned directly from fleet data, enabling outlier-based anomaly detection without physical modeling or extensive calibration. Multi-bin spatial validation (uniformly placed across Peak Torque RPM [22]) and temporal validation (five consecutive 1-hour windows) distinguish genuine faults from fleeting effects, maintaining robustness under dynamic conditions. Requiring only standard OBD data, the approach scales immediately to heterogeneous vehicle fleets for predictive maintenance.

III. System Overview and Methodology

The proposed methodology detects and predicts anomalies in Fuel Rail Pressure (FRP) under real-world operating conditions by leveraging real-time sensor data and a Gaussian Mixture Model (GMM) based outlier detection framework.

A. Data Acquisition

Vehicle sensor data is collected in real time through the On-Board Diagnostics (OBD) interface using a proprietary telematics device (Intangles Lab's product) [23]. The key parameters include Fuel Rail Pressure (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.

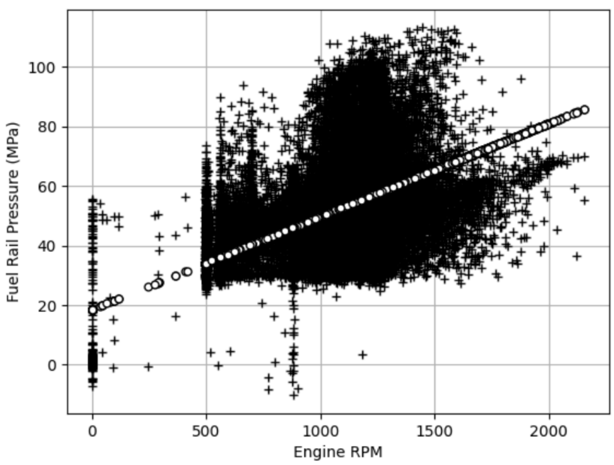

Fig. 1: Correlation Plot depicting positive correlation between RPM and FRP

Under typical engine operation, FRP varies significantly with engine RPM: lower RPM, load, and throttle (idle conditions) correspond to reduced fuel rail pressure demand, while higher RPM and load conditions require elevated pressure to ensure adequate fuel delivery for combustion. To minimize this variability, FRP values are analyzed only when the engine is at peak torque RPM (as per manufacturer specifications), with 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 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 is illustrated by the scatter plot in Figure 1, where a fitted regression line with a positive slope indicates that FRP increases with RPM. The scatter plot reveals that FRP measurements at any given RPM follow an approximately Gaussian distribution, with data points concentrated around a central trend line and tapering off symmetrically toward the extremes. The Gaussian-like spread around the mean FRP-RPM relationship reflects natural variability in fuel demand due to factors such as instantaneous load changes, throttle variations etc. This distributional characteristic provides the theoretical foundation for applying Gaussian Mixture Models to characterize normal FRP behavior and detect anomalies as deviations from this expected distribution. In contrast, Engine Load and Accelerator Pedal Position showed weak or inconsistent relationships with FRP, making them unsuitable as primary predictors. Therefore, Engine RPM was selected as the key feature for FRP modeling and anomaly detection.

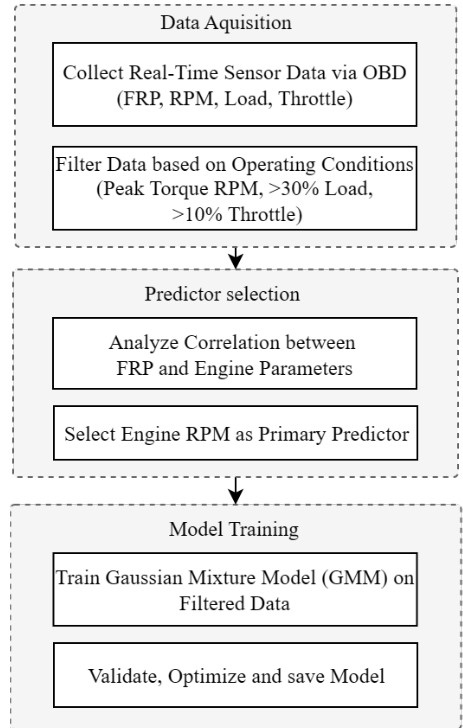

Fig. 2: Block Diagram for proposed Model Building

C. Proposed Algorithm

The proposed anomaly detection approach is based on a Gaussian Mixture Model (GMM) 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. 2, while the steps for anomaly prediction during inference time is shown in Fig. 3. This algorithm comprises the following steps:

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

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

  where K is the number of Gaussian components used in the mixture for each bin.
  This approach allows capturing the natural multimodal variability in FRP across different RPM ranges better than a single Gaussian distribution. The parameters μ_j and σ_j from each GMM component serve as a statistical baseline to detect deviations representing anomalies in FRP behavior.

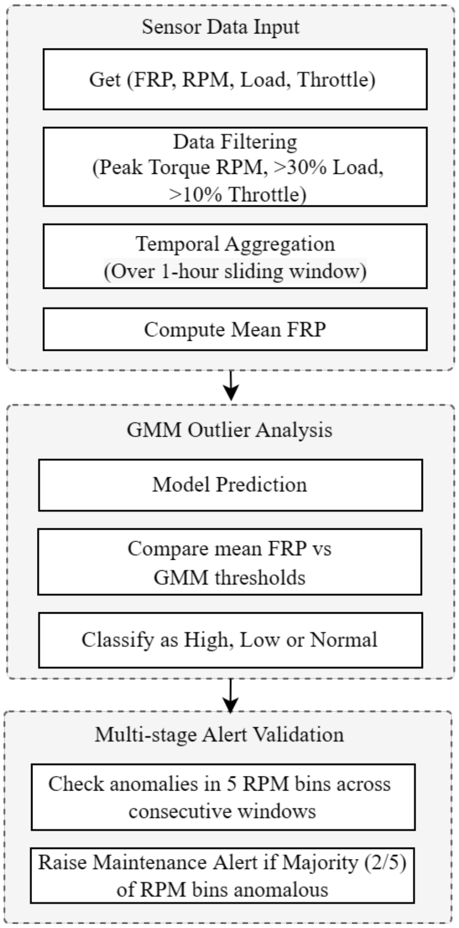

Fig. 3: Pipeline for anomaly prediction during inference time

- **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 were empirically tuned to balance detection sensitivity and false alarm rates.
- **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

The results and predictions of the proposed algorithm are validated against a linear regression model trained on normal operating data, where all system states are healthy, to establish 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 Diagnostic Trouble Codes (DTCs) provided by the Engine Control Unit (ECU), demonstrating its effectiveness in real-world applications.

Validation was performed using vehicles exhibiting specific Diagnostic Trouble Codes (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 Gaussian Mixture Model (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 12,000 to 15,000 cc and power output between 400 and 600 hp.

A. Gaussian Mixture Model Validation

The proposed GMM-based anomaly prediction algorithm was 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 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. This could be attributed to variations in fault manifestation across different vehicle operating profiles or thresholds (multiplicative factor for σ) being too stringent.

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. This false positive behavior may stem from edge-case operating conditions that deviate from the learned normal distribution or inherent overlap between normal variability and anomalous patterns at the distribution boundaries.

Table III presents the lead time between predictive alerts and DTC occurrence for both high and low FRP scenarios for GMM as the model.

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) [15]. 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.

TABLE I: Performance comparison of GMM and LR models across different FRP conditions

FRP-type	Methods	No. Of Test Vehicles	No. Of Vehicles with Alerts	No. Of 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 II: Performance metrics of GMM and LR models across different FRP conditions

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

Table I 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 II. Overall GMM demonstrates superior performance compared to the baseline model across all the situations of High, Low and Normal FRP.

V. Conclusion

The comparative evaluation of GMM and LR approaches for FRP anomaly prediction demonstrates the superior performance of GMM in generating early and reliable alerts. Validation using DTCs confirmed that alerts labeled high and low frp alerts consistently preceded actual fault occurrences, demonstrating the model's predictive capability. The results validate the practicality of unsupervised normal-behavior modeling for early fault detection. Furthermore, the multi-stage alert validation mechanism employing multiple RPM bins over consecutive windows demonstrated the algorithms ability to reduces false positives, enhancing the effectiveness of real-time monitoring.

VI. Future Scope

While the unsupervised approach demonstrates strong performance, future research should explore hybrid architectures that incorporate limited labeled fault data. Comparative studies between purely unsupervised models and supervised or semi-supervised alternatives could further quantify the performance trade-offs and identify optimal modeling strategies for different data availability scenarios. Additionally, extending the framework to incorporate multiple correlated sensor signals (e.g., fuel temperature) may enhance predictive accuracy.

TABLE III: 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

ACKNOWLEDGMENT

This research was fully supported by Intangles Lab Pvt. Ltd., Pune, India. We thank our colleagues from Intangles Lab, who provided the required data insights and expertise that greatly assisted the research.

REFERENCES

[1] M. Young, *The Technical Writer's Handbook*. Mill Valley, CA: University Science, 1989.

[2] Robert Bosch GmbH, *Diesel-Engine Management: Systems and Components*. Warrendale, PA: SAE International, 2014.

[3] R. Payri, F. J. Salvador, J. Gimeno, and J. De la Morena, ”Effects of nozzle geometry on direct injection diesel engine combustion process,” *Applied Thermal Engineering*, vol. 31, no. 17-18, pp. 4209–4218, 2011.

[4] K. Kim, D. Kim, Y. Jung, and C. Bae, ”Spray and combustion characteristics of gasoline and diesel in a direct injection compression ignition engine,” *Fuel*, vol. 182, pp. 616–626, 2016.

[5] G. Stumpp and M. Ricco, ”Common rail-an attractive fuel injection system for passenger car DI diesel engines,” *SAE Technical Paper* 960870, 1996.

[6] N. A. Henein, M. C. Lai, I. P. Singh, L. Zhong, and J. Han, ”Characteristics of a common rail diesel injection system under pilot and post injection modes,” *SAE Technical Paper* 2001-01-0606, 2001.

[7] A. E. Catania, A. Ferrari, M. Manno, and E. Spessa, ”Experimental investigation of dynamics effects on multiple-injection common rail system performance,” *Journal of Engineering for Gas Turbines and Power*, vol. 130, no. 3, p. 032806, 2008.

[8] G. Hong, H. Zhao, and B. Liang, ”Fuel injection pressure effects on performance and emissions of a diesel engine with high pressure common rail injection system,” *SAE Technical Paper* 2004-01-0928, 2004.

[9] B. Fan et al., ”Effect of injection pressure on the spray characteristics of dimethyl ether in a common rail fuel injection system,” *Energy Conversion and Management*, vol. 157, pp. 494–501, 2018.

[10] G. M. Bianchi, P. Pelloni, F. E. Corcione, and F. Luppino, ”Numerical analysis of high-pressure fast-response common rail injector dynamics,” *SAE Technical Paper* 2001-01-0211, 2011.

[11] H. Ando, S. Takemura, K. Koyanagi, and J. Senda, ”Analysis of common rail type fuel injection system,” *JSAE Review*, vol. 23, no. 3, pp. 297–304, 2009.

[12] ”What Happens If Your Fuel Pressure Is Too High?, ”https://www.autoscopecarcare.com/car-tips/what-happens-if-your-fuel-pressure-is-too-high, accessed Oct. 17, 202

[13] N. Guerrassi and P. Dupraz, ”A common rail injection system for high speed direct injection diesel engines,” *SAE Technical Paper* 980803, 2007.

[14] L. Baika, N. Henein, and W. Bryzik, ”Investigation of injector coking and its effect on injection characteristics in diesel engines,” *SAE Technical Paper* 2015-01-0865, 2015.

[15] K. Kasmaoui, ”Linear Regression,” in *Global Encyclopedia of Public Administration, Public Policy, and Governance*, A. Farazmand, Ed. Springer, Cham, 2019, doi: 10.1007/978-3-319-31816-5_478-1.

[16] Common Rail Wikipedia https://en.wikipedia.org/wiki/Common_rail

[17] European Emission Standardshttps://en.wikipedia.org/wiki/European_emission_standards

[18] European Emission Standards https://www.transportpolicy.net/standard/eu-heavy-duty-emissions/

[19] Common Rail Fuel Injection https://dieselnet.com/tech/diesel_fi_common-rail.php

[20] what-is-common-rail-system https://dieselnet.com/tech/diesel_fi_common-rail.php

[21] Common Rail Useful Information https://www.perkins.com/en_GB/network-resources/useful-information/common-rail.html

[22] Power Band https://en.wikipedia.org/wiki/Power_band

[23] Intangles Ingenious https://www.intangles.ai/wp-content/uploads/2024/10/Ingenious-EC200-Device-Manual-05-09-24_TM_compressed_south_asia.pdf