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Adaptive Gradient Boosting for Fuel Consumption Prediction in Mining Haul Trucks under Concept Drift Monitoring

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Abstract

Fuel consumption prediction models deployed in mining operations often degrade in performance due to changes in the distribution of high-frequency telemetry data, a phenomenon commonly associated with concept drift. Static machine learning models trained on historical data may therefore lose reliability over time in dynamic operational environments. This study aims to develop an adaptive regression approach for predicting fuel consumption in mining haul trucks by integrating a Gradient Boosting Regressor with batch-wise performance monitoring and periodic retraining. Real-world telematics data were processed through systematic preprocessing and feature engineering to derive behavioral and operational indicators relevant to fuel usage. Model performance was evaluated using Mean Absolute Error (MAE), Mean Squared Error (MSE), and the coefficient of determination (R^2), while drift monitoring employed a threshold-based MAE analysis over streaming batches. Experimental results show that the initial model achieved an MAE of 27.27 L/h and an R^2 of 0.759, and the adaptive retraining strategy provided marginal yet consistent performance stabilization without detecting significant drift within the observed period. Beyond the mining application, this framework contributes to the development of lightweight adaptive regression systems for real-time data stream processing, supporting computationally efficient predictive maintenance in industrial IoT environments.

Keywords : *adaptive gradient boosting, behavioral indicators, concept drift detection, fuel consumption, mining haul trucks*

1. INTRODUCTION

Enhancing vehicle fuel economy is a crucial component of sustainable transportation systems globally [1]. This initiative is motivated by essential environmental, economic, and geopolitical considerations [2]. The transportation sector significantly contributes to greenhouse gas emissions, and enhancing fuel efficiency directly mitigates the carbon of transportation fleets, including heavy-duty industrial vehicles [3], [4]. From an economic standpoint, fuel efficiency offers substantial cost reductions for consumers and industries, particularly in the context of volatile global fuel prices [5], [6].

An accurate forecast of fuel use is essential to attain this objective. Dependable predictive models facilitate the optimization of multiple facets, including vehicle design by manufacturers, driving methods, and fleet route planning [7], [8]. The primary issue in precisely forecasting fuel usage resides in the intricacy and multitude of elements that affect it. The factors are categorized into three primary domains: vehicle performance and intrinsic parameters (e.g., engine capacity, mass, vehicle classification), driving behavior (e.g., acceleration, velocity, driving style), and operating environment (e.g., road conditions, meteorological factors, road incline) [7], [9], [10]. Due to the intricate interplay among these aspects, data-driven models employing machine learning (ML) have emerged as the

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predominant and most efficacious method [5], [9]. Recent studies have emphasized the role of data-driven approaches in identifying abnormal fuel consumption patterns within fleet operations. An unsupervised machine learning framework based on Isolation Forest, combined with visual verification techniques, has been applied to detect fuel consumption anomalies in logistics fleets, demonstrating practical applicability in real-world operational settings [11]. These findings highlight the importance of monitoring mechanisms to detect deviations in fuel usage behaviour.

Despite the considerable success of machine learning models in forecasting fuel usage, their efficacy frequently diminishes over time [12]. This issue stems from the fundamental assumption of most machine learning models, specifically that the training data originates from a steady or invariant distribution [13]. However, such stationarity assumptions are rarely satisfied in real-world industrial and transportation data streams [14], [15]. The operational environment of vehicles is dynamic, resulting in alterations to the statistical features of the underlying data. This occurrence is referred to as concept drift [16].

Conceptual drift formally refers to the alteration of the joint probability distribution of input variables (X) and target variables (y) over time ($P_t(X, y) \neq P_{t+1}(X,y)$) [17], [16]. This alteration may arise from a variation in the distribution of input features, referred to as virtual drift, or a modification in the conditional probability of the output contingent upon the input ($P(y|X)$), known as genuine drift [13], [17]. Consequently, models trained on past data become obsolete and imprecise when applied to fresh data, resulting in a decline in predicting performance [12], [16]. In terms of fuel consumption, drift may be induced by alterations in driver behavior, vehicle modifications, route changes, or the deterioration of engine components over time [18], [19]. In the absence of an appropriate detection and adaptation mechanism, predictive models operating on streaming telemetry data are prone to progressive performance degradation [20].

This issue is addressed through three primary connected research pillars. Initially, in the realm of fuel consumption modelling, data-driven methodologies have emerged as predominant, characterized by the extensive utilization of diverse algorithms like Support Vector Machine (SVM), Random Forest (RF), Artificial Neural Networks (ANN), and Long Short-Term Memory (LSTM) [7], [21], [22], [9]. These models proficiently leverage extensive vehicle operational data, often obtained from On-Board Diagnostics (OBD) systems and Controller Area Network (CAN bus), to dynamically capture essential variables [23], [22].

Secondly, the efficacy of these models is undermined by the occurrence of concept drift, which has emerged as a recognized field of study. The primary detection methods examined in the literature encompass techniques that track the model error rate, including the drift detection method [13], and data window-based approaches like adaptive windowing, which adaptively modifies the observation window size to identify distributional changes [24]. Third, numerous adaptive learning mechanisms have been suggested to mitigate drift. The methodologies encompass periodic model retraining with the most recent data in a sliding window to more advanced incremental and online learning techniques that provide continuous model updates [25].

Moreover, ensemble approaches have demonstrated efficacy as a robust tool for adaptation, either by modifying the weights of individual ensemble constituents or by substituting underperforming members [13], [17]. Contemporary adaptive frameworks, shown by their application to maritime fuel use, have proven the efficacy of "rolling retraining" and "dual adaptation" methodologies in addressing the dynamics of real-world data [25].

Although prior studies have demonstrated the effectiveness of machine learning for fuel consumption modeling and adaptive mechanisms for concept drift mitigation, several limitations remain. Many fuel prediction studies assume relatively stable data distributions and do not incorporate systematic drift monitoring in regression settings. Conversely, adaptive learning research often

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emphasizes classification tasks or computationally intensive detectors, which are less suitable for high-frequency industrial telemetry. In mining-specific contexts, studies primarily focus on operational optimization without integrating structured behavioral–operational feature taxonomy with lightweight performance-based drift monitoring. A recent systematic review on adaptive machine learning for fuel efficiency optimization in open-pit mining trucks further reported that only a limited proportion of studies explicitly incorporate driver behavioral indicators into adaptive modeling frameworks, highlighting the lack of lightweight, deployable regression-oriented solutions tailored to mining telemetry environments [26]. Therefore, a methodological gap persists in developing a computationally efficient adaptive regression framework tailored to mining haul truck telemetry.

To address this gap, this study proposes an adaptive gradient–boosting framework for predicting fuel consumption in mining haul trucks. The objectives are threefold, (1) to systematically identify behavioral and operational indicators derived from high-frequency telemetry data; (2) to integrate regression modeling with batch-wise performance monitoring for detecting potential distributional shifts; and (3) to evaluate periodic retraining as a lightweight adaptive learning strategy. The contributions include a structured feature taxonomy for mining fuel modelling, a practical, performance-aware drift-monitoring scheme, and empirical validation of adaptive retraining using real-world mining telemetry data. Beyond its domain application, this framework advances lightweight adaptive regression for real-time industrial data streams, emphasizing computational efficiency and deployment feasibility in resource-constrained environments. Accordingly, the novelty of this work lies in operationalizing a lightweight adaptive regression loop (monitor–retrain–evaluate) tailored to mining telemetry streams.

2. METHOD

This section presents the methodological workflow for developing and evaluating the proposed adaptive gradient boosting framework. It covers dataset description, data preprocessing (including handling missing values, outlier treatment, feature engineering, and transformation), identification of behavioral and operational indicators, initial model development, concept drift detection, adaptive retraining, and performance evaluation. The overall workflow of the proposed framework is summarized in Figure 1.

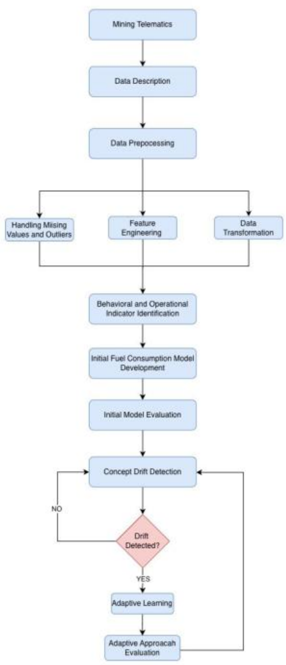

Figure 1. Adaptive fuel prediction framework with drift monitoring

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2.1. Data Description

The dataset used in this study contains 71 features that reflect various operational parameters and behavior of heavy vehicles in the context of mining activities. The data includes time information, vehicle and operator identity, engine conditions, temperature and pressure variables, and signals and geographic indicators recorded during the operating period. This dataset, as shown in Table 1, contains various important features that can be categorized into several main groups based on their functions according to the research to be conducted. The following is a feature classification table of the dataset used.

Table 1. Dataset feature classification

Category	Feature	Description
Identity and Time	id,reporttime, datecreated, dtcrtonbd, hiveperiod, hivesite	The system provides a unique ID, records a timestamp for reporting and logging, and divides the time and location information into Hive data.
Unit and Operator	mobileid, mobiletypeid, egi, opr_nrp, opr_shift, asg_loaderid, asg_lock	The information includes the vehicle unit ID, the type and model of heavy equipment, the IDs of the operator and loader pair, and the shift information.
Status and Activity	mobilestatusgroupid, mobilestatusid, mobileactivityid, plm_status	Unit status & activity categories such as traveling, hauling, loading, stopped, and dumping.
Engine Parameters	eng_speed, blowby_pres_pm, boost_press, eng_oil_press, eng_oil_temp, cool_temp,	Engine technical data: speed, pressure, oil temperature, and coolant temperature.
	fuel_rate_011, fuel_injection, tm_oil_temp, ambient_air_temp, atomos_press	Fuel consumption rate (L/h), fuel injection, transmission oil temperature, ambient air temperature
Control and Behavior	accel_pos, hoist_lever_pos, retarder_pos, foot_brake_pos, shift_indicator, lu_on, eco_on	Driver control indicators: accelerator, brake, hoist lever, retarder, gear status & lock-up clutch, and Fuel-saving mode usage time
Vehicle Sensors	plm_speed, tm_out_speed, plm_payload, plm_inc, odometer_s, standard_smr, fuel_level_tm	The payload meter sensor provides information on speed, load, inclination, mileage, runtime, and fuel level.
Temperature and Pressure Sensors	tc_oil_temp, retarder_f_oil_temp, retarder_r_oil_temp, plm_rf, plm_lf, plm_rr, plm_lr, calc_weight	Temperatur Various components' oil temperature and pressure are monitored, along with the estimated weight of the vehicle.
Location Data (GPS)	pos_lon, pos_lat, pos_alt, pos_speed, pos_dir, pos_gpssignal, pos_wifisignal	The system also records the geographic position, GPS speed, direction, and the quality of the GPS/WiFi signal.
Alarms	alr_isoverload, alr_isoverspeed, alr_ismisroute	Abnormal condition alarms, such as overload, overspeed, or wrong route.
Location and Geospatial	pos_gid, pos_type, pos_name, pos_regionid, postmode	Worksite ID and name, position type, region/pit area, and data posting mode.

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The data were collected from an open-pit mining operation in Indonesia. Overall completeness was high (near 100% non-null for most variables). Only a small fraction of missing values (<0.1%) occurred in a few identity-related fields (e.g., opr_nrp and asg_loaderid), which did not materially affect the analysis.

2.2. Data Preprocessing

The data pre-processing stage is a fundamental step in ensuring the quality and readiness of data before entering the modeling stage. This is very important in the context of time series sensory data, where data continuity, consistency, and validity greatly affect the analysis results. The pre-processing process in this study involves several main stages, including handling missing values, outlier detection, feature engineering, and data transformation.

2.2.1. Handling Missing Values and Outliers

In handling missing values on continuous features such as eng_speed and boost_press, time-based interpolation methods such as linear interpolation and time-weighted interpolation are used. This method allows estimating missing values by considering the tendency of previous and subsequent values in the context of time, thus providing a more realistic approach compared to simple imputation techniques such as mean or median [27]. Meanwhile, for categorical features, an imputation approach using the mode value is applied because it can maintain the distribution of the dominant category.

Outlier value detection is performed using a combination of statistical techniques and domain-based rules. Statistically, the interquartile range (IQR) and Z-score methods are used to detect data that deviates significantly from the normal distribution [28], [29]. Statistical analysis is complemented by the application of practical rules based on domain knowledge, such as eliminating negative values in the plm_speed feature or limiting the fuel_rate_011 value so that it does not exceed the maximum technical capacity of the engine. This combination is effective in suppressing data representation errors without eliminating operationally valid extreme values [30].

2.2.2. Feature Engineering

To improve the data representation capability, the approach creates time-based features by extracting the time component from the reporttime column into features such as hours of the day, days of the week, and time categories. This temporal information is relevant considering the variation in environmental conditions and operational activities that tend to be influenced by time.

In addition, derived features are also developed; acceleration is calculated as the change in plm_speed value with respect to time, which reflects the dynamic load on the engine. This variable is highly correlated with fuel consumption. Statistical features such as rolling average and rolling standard deviation are also applied to key variables such as eng_speed, accel_pos, and fuel_rate_011 in a certain time window. This technique is useful in reducing noise from sensors and capturing short-term patterns effectively [31]. Table 2 presents a representative sample of the engineered features derived from the preprocessing stage. These variables were computed from high-frequency telemetry data to capture temporal dynamics and instantaneous operational changes.

As shown in Table 2, the results are created to enrich the contextual information and operational behavior of vehicles. Several new features are derived from the raw data using a time- and sequence-based feature engineering approach. Several new variables are developed to capture the temporal dynamics and behavior of vehicles that are not explicit in the original features. The report_hour and report_day_of_week features are extracted from the reporttime column to identify operational patterns based on time, which can affect fuel consumption due to variations in workload and environmental conditions at certain hours or days. The time_diff_seconds feature is calculated as the time difference

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between two consecutive reports after the data is sorted by vehicle and time and is used as a proxy for activity_segment_duration_sec, which is the duration of an activity segment. In addition, speed_change reflects the change in speed from the previous report, which serves as an indicator of acceleration and deceleration patterns.These features collectively provide additional information that can help detect changes in operational behavior and identify potential concept drift in the fuel consumption model**.**

Table 2. Sample Output of Engineered Features

Index	reporttime	report_hour	report_day_of_week	time_diff_seconds	speed_change	activity_segment_duration_sec
185331	2024-06-01 01:10:39.260	1	5	0.000	0.000000	0.000
496213	2024-06-01 01:10:45.260	1	5	6.000	-2.357596	6.000
65665	2024-06-01 01:10:57.260	1	5	12.000	5.522664	12.000
666843	2024-06-01 01:11:00.260	1	5	3.000	0.551896	3.000
474531	2024-06-01 01:11:03.323	1	5	3.063	-0.990820	3.063

2.2.3. Data Transformation

Temporal fields such as reporttime are converted into proper datetime formats to support time-aware operations including resampling, windowing, and temporal joins. Categorical variables are transformed into numerical representations, with techniques such as one-hot encoding applied where required by downstream machine learning models. This step ensures compatibility with algorithms that assume numerical input spaces.

2.3. Identification of Behavioral and Operational Indicators

For the purpose of operational behavior analysis and fuel consumption modeling, the features in this dataset are classified into three main groups, including behavioral indicators, operational indicators, and target variables. This grouping aims to separate the direct influence of operator actions on the vehicle from the influence of the working environment and operational system status, thus allowing for more interpretive modeling and supporting contextual concept change detection.

Behavioral indicators reflect how the vehicle is operated directly by the operator. Features included in this category are pos_speed, eng_speed, accel_pos, speed_change, and mobileactivityid. These five features capture aspects of vehicle responsiveness to operator input and driving behavior dynamics, which directly contribute to fuel consumption patterns.

Meanwhile, operational indicators represent the vehicle's working context, environmental conditions, system status, and administrative elements that are not directly affected by operator actions but have a significant impact on efficiency and work patterns. Features included in this category include plm_payload, pos_regionid, time_diff_seconds and activity_segment_duration_sec, report_hour and report_day_of_week, as well as mobileid, opr_nrp, and asg_loaderid, which indicate the identity of the

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unit, operator, and loader. In addition, geospatial information such as pos_gid, pos_type, and pos_name, as well as compliance indicators such as alr_ismisroute and system status mobilestatusgroupid and mobilestatusid, are also classified as part of operational indicators. These features provide a comprehensive picture of the working environment, actor roles, and physical and administrative conditions in which the vehicle operates.

The main target variable in this study is fuel_rate_011, which is the rate of fuel consumption in liters per hour (L/h). This variable was chosen because it reflects the vehicle's energy performance quantitatively and is the focus in developing an adaptive model of fuel consumption based on behavior and operations.

2.4. Initial Fuel Consumption Model Development

The fuel consumption prediction model is developed by utilizing a subset of features consisting of behavioral indicators, operational indicators, and target variables, namely fuel_rate_011. Modeling is done using the Gradient Boosting Regressor (GBR) algorithm, a decision tree-based ensemble method that combines several weak learners sequentially to minimize prediction errors gradually. The general formula for GBR at the mth iteration is shown in Equation 1.

$$\mathbf{F_m(x) = F_{m-1}(x) + y_m h_m(x)} \tag{1}$$

where $\boldsymbol{F_m}$(x) is the joint model up to the mth iteration. $\boldsymbol{h_m(x)}$ is the mth regression tree trained on the negative gradient of the loss function, and $\boldsymbol{y_m}$ the learning rate that governs the contribution of the new tree to the overall model. This approach has been shown to be effective in handling tabular data with non-linear relationships and complex interactions between features [32]. Then the data is split using a time-based split approach, where the data is sorted by reporttime, then split into an initial 80% for training and a final 20% for testing. This approach preserves the natural temporal structure and avoids leakage of future data into training, as is the practice in time series data modeling [33]. Next, the model is trained using the feature matrix and target transformed results $(\boldsymbol{X_{train}}, \boldsymbol{y_{train}})$ and evaluated on the testing data $(\boldsymbol{X_{test}}, \boldsymbol{x_{test}})$ using three main evaluation metrics, namely Mean Absolute Error (MAE), Mean Squared Error (MSE) and R-squared $(\mathbf{R^2})$ with the equation below.

$$\mathbf{MAE = \frac{1}{n} + \sum_{n=1}^{n} |y_i - \hat{y}_i|} \tag{2}$$

$$\mathbf{MSE = \frac{1}{n} + \sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{3}$$

$$\mathbf{R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y}_i)^2}} \tag{4}$$

As defined in Equation (2), MAE measures the average absolute difference between the actual and predicted values, thus providing a direct estimate of the magnitude of the error. MSE, as in Equation (3), imposes a quadratic penalty on the error, making it more sensitive to extreme predictions or outliers. Meanwhile, R^2 calculated using the equation in Equation (4) shows how much of the variance in the target data can be explained by the model. These three metrics collectively provide a comprehensive picture of the model's accuracy, generalization ability, and stability [34].

2.5. Concept Drift Detection

This study employs a periodic model performance monitoring approach to identify potential concept drift in the data stream. The primary objective is to assess the predictive stability of the Gradient

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Boosting Regressor model when applied to chronologically ordered test data. To simulate streaming conditions, the test dataset is partitioned into fixed-size batches of approximately 1000 observations. Model performance is evaluated for each batch using the Mean Absolute Error (MAE).

Concept drift is indicated when the MAE value of a given batch exceeds a predefined threshold, suggesting a potential degradation in predictive performance due to changes in the underlying data distribution or feature-target relationships. To formally define this threshold, let $MAE_{initial}$denote the Mean Absolute Error obtained during the initial validation phase of the model. The drift threshold T, representing the maximum acceptable MAE before a potential drift signal is triggered, is determined as:

$$T = MAE_{initial} \times (1 + \alpha) \tag{5}$$

In equation (5) where α represents a tolerance margin. In this study, $\alpha = 0.20$, reflecting a relative performance degradation tolerance appropriate for regression tasks in industrial telemetry environments. This formulation follows a relative error tolerance criterion rather than a formal statistical bound. The selected threshold is intended to capture meaningful performance deviations while preserving computational simplicity.

The monitoring process is conducted iteratively, and the MAE value of each batch is recorded along with its corresponding drift status. The monitoring results are visualized through a temporal performance graph, highlighting batches that exceed the defined threshold. This approach falls within the category of performance-aware drift detection methods, which are effective for regression tasks in data stream environments [35], [36]. This approach provides a solid foundation for understanding the dynamics of model degradation in real time and forms the basis for subsequent model adaptation strategies.

2.6. Adaptive Learning

To overcome the challenge of concept drift that can reduce prediction accuracy over time, this study implements an adaptive learning approach based on periodic retraining so that the model can adjust to the dynamics of changing data distributions. We set the retraining trigger deterministically, meaning that the model automatically retrains after every 25 batches of test data. The retraining interval (25 batches) was selected as a practical trade-off between adaptation responsiveness and computational overhead, consistent with periodic update strategies in stream mining [37], [38].

At each retraining point, a new model is initialized and retrained using a combination of the initial training data and all batches of test data that have been processed up to that point. This approach allows the model to capture new patterns that are not available in the initial training data without completely ignoring historical information. This scheme is considered effective for maintaining predictive performance in environments with gradual or intermittent concept changes.

2.7. Adaptive Approach Evaluation

The effectiveness of the adaptive learning strategy was evaluated by monitoring the performance of the batch-updated model, including batches processed after each retraining cycle. This evaluation used a temporal scoring scheme, allowing analysis of predictive stability across changing data conditions.

To measure the impact of adaptation, the average MAE across all processed batches of the adaptive model was compared with the baseline model without retraining. Additionally, three regression performance metrics, including MAE, MSE, and coefficient of determination (R^2), were calculated across the entire testing dataset using the final adaptive model, which is defined as the model obtained after completing all retraining cycles. These results were directly compared with the performance of the

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initial single-training baseline model to assess whether periodic retraining improved predictive robustness under conditions of potential concept drift.

3. RESULT

3.1. Descriptive Data Analysis

We conducted descriptive analysis on a number of main variables, including behavioral indicators, operational indicators, and fuel consumption target variables, as shown in Table 3.

Table 3. Descriptive Statistics of Selected Variables

Statistic	fuel_rate_011	report_hour	report_day_of_week	time_diff_seconds	speed_change	activity_segment_duration_sec
Count	695,552	695,552	695,552	695,552	695,552	695,552
Mean	106.648	11.474	3.164	111.285	0.000844	111.285
Std	81.863	6.899	2.001	1,412.304	7.518	1,412.304
Min	0.000	0.000	0.000	0.000	-56.712	0.000
25%	8.800	5.000	1.000	3.037	-2.437	3.037
50%	115.000	11.000	3.000	6.296	0.1148	6.296
75%	187.300	17.000	5.000	36.096	2.482	36.096
Max	233.000	23.000	6.000	509,142.173	58.749	509,142.173

The main variables in Table 3 show significant variations in vehicle behavior and operational conditions. We recorded the average fuel consumption (fuel_rate_01l) at 106.65 L/h with a high deviation, indicating a wide distribution and varying working conditions. The reporting time value (report_hour) was evenly distributed throughout the day, with an average occurring around 11: 00, while the distribution of reporting days (report_day_of_week) was quite balanced in a week. The duration between reports (time_diff_seconds) has a very wide range, from zero to more than 509 thousand seconds, indicating significant variations in the frequency of data recording. Meanwhile, the speed change (speed_change) was mostly close to zero, but with quite extreme outliers, indicating fluctuating operational dynamics.

3.2. Analysis of Fuel Consumption

In terms of distribution, the target variable fuel_rate_01l shows an abnormal distribution pattern and is very skewed to the right, as shown in Figure 3.

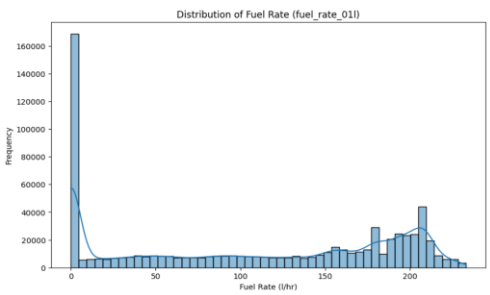

Figure 3. Distribution of Fuel Rate

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The visualization results of Figure 3 show a high frequency accumulation at fuel consumption values approaching zero, which most likely reflects the condition of the engine being inactive or idle. In addition, the distribution has several peaks (multi-modal), especially in the range of 50 to 230 L/h, which indicates the existence of vehicle operation segments with different fuel consumption patterns. This pattern illustrates the complexity of operational activities for heavy equipment, which vary based on factors such as workload, engine status, and operating environment. This abnormality in distribution can be associated with the concept drift phenomenon, where fuel consumption patterns change over time as workload, terrain, or driver behavior changes.

By observing a significant temporal pattern in fuel usage behavior when we look at the average fuel consumption by time of day. Figure 4 shows the left graph; the average fuel consumption by hour of the day shows a clear fluctuation, with a significant increase starting at 07:00 and reaching a peak around 12:00 to 13:00. This pattern indicates an increase in vehicle operational activity during the main working hours and a possible decrease again after the lunch break. We can attribute the increase in consumption during these hours to a more intensive workload and denser traffic conditions.

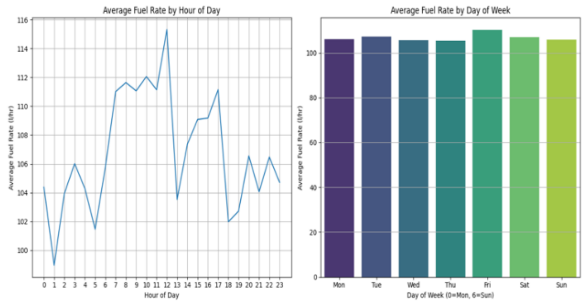

Figure 4. Average fuel consumption by time of day

The bar graph on the right illustrates the average daily fuel consumption for each day of the week. Friday exhibits the highest fuel consumption, succeeded by Tuesday and Saturday, whereas Sunday demonstrates a lower consumption rate. This disparity can be ascribed to fluctuations in operational load across days, including heightened activity during weekends or diminished activity on holidays. Identification of concept drift, wherein temporal variations such as weekly workload fluctuations or alterations in operational policies may induce distribution changes that affect the predictive model's accuracy if not dynamically adjusted.

Furthermore, the results of the fuel consumption analysis, namely the relationship between fuel consumption and vehicle speed, show a significant correlation pattern. As seen in Figure 5, based on a data sample of 5,000, the scatter plot illustrates the relationship between fuel_rate_011 with pos_speed and eng_speed. Fuel consumption increases with increasing position speed, especially at medium to high speeds. A stronger relationship is seen between fuel consumption and engine rotation speed, where increasing RPM shows a trend of increasing consumption. This finding is consistent with the operational characteristics of diesel engines, which are more wasteful of fuel when the workload increases.

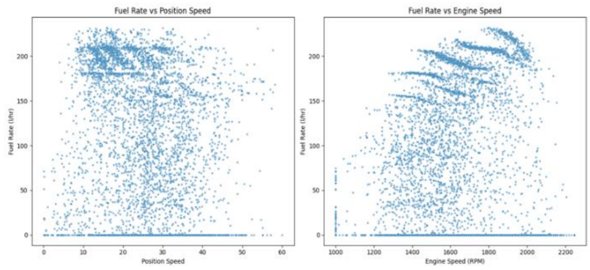

Figure 5. Relationship between fuel consumption and vehicle speed

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These results improve our understanding of how fuel consumption changes with vehicle behavior and highlight the need to include operational indicators like pos_speed and eng_speed as important factors in predictive algorithms, particularly for spotting changes in patterns (concept drift) caused by shifts in vehicle operation over time.

An analysis of fuel consumption distribution by Mobile Activity ID and Position Region ID reveals substantial variations among categories. Figure 6 illustrates that activities with specific IDs exhibit consistently elevated fuel consumption compared to others, suggesting greater workloads or operational conditions for those activities. The regional distribution indicates variability in consumption, with certain areas, specifically Region ID 7 and ID 8, exhibiting elevated consumption levels and extensive distribution ranges. These findings underscore the significance of incorporating activity and location variables in assessing vehicle operational efficiency.

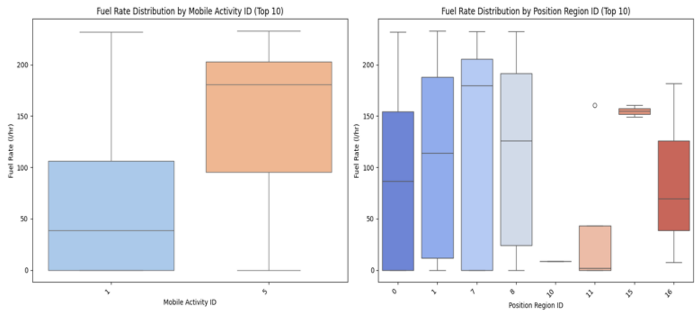

Figure 6. Fuel Rate Distribution Top 10

An exploratory correlation analysis was conducted on key numerical variables obtained from onboard telemetry to enhance understanding of the operational dynamics influencing fuel consumption in open-pit mining trucks. Figure 7 presents the correlation matrix, displaying the Pearson coefficients between fuel_rate_01l (fuel consumption rate) and various behavioural and operational parameters, such as accel_pos, eng_speed, pos_speed, and plm_payload.

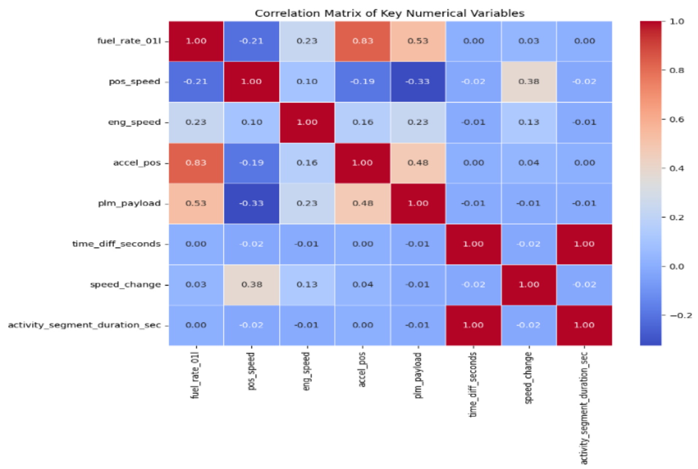

Figure 7. Correlation matrix of key numerical features related to fuel consumption

The analysis demonstrates a significant positive correlation between fuel consumption and accelerator pedal position (r = 0.83), suggesting that increased throttle pressure by the operator directly results in higher fuel usage. This is consistent with the principles of combustion engine mechanics, in which fuel injection correlates with engine load and driver input. Furthermore, payload weight exhibits a moderate positive correlation (r = 0.53), indicating that increased load necessitates higher engine

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output and, as a result, greater fuel consumption during haul cycles. Engine speed (r = 0.23) and speed change (r = 0.03) exhibit weak correlations with fuel rate, indicating that instantaneous RPM and acceleration variation are likely secondary factors, influenced by interactions with other variables. Vehicle GPS speed (pos_speed) shows a slight negative correlation (r = -0.21) with fuel consumption.This phenomenon may be ascribed to low-speed phases occurring during idling, queuing, or loading operations, wherein the engine persists in fuel combustion without substantial distance being traversed.

Additional temporal features, including time_diff_seconds and activity_segment_duration_sec, exhibit negligible correlation with fuel consumption in linear terms. Nonetheless, these variables may still induce nonlinear interactions, thereby warranting their inclusion in model training for nonlinear ensemble learners such as Gradient Boosting–based regressors.

This exploratory analysis emphasises the significance of driver behaviour (accel_pos) and load factors (plm_payload) as primary contributors to variations in fuel efficiency. The strong correlation among these dimensions supports their application as leading indicators in real-time fuel prediction models. The results support the hypothesis that variations in operator driving style or operational loads, observed over time, can lead to concept drift in the relationship between inputs and fuel usage, necessitating adaptive learning methods to sustain predictive accuracy.

3.3. Initial Fuel Consumption Model Performance

Table 4. Initial Model Evaluation

Evaluation Components	Value	Description
Total Amount of Data	695,552 rows	After preprocessing and encoding
Number of Features	57 columns	Includes behavioral, operational, and temporal features
Training Set Size	556,441 rows	80% of total data used for model training
Testing Set Size	139,111 rows	20% of total data used for model evaluation
Training Period	until 2024-06-07 02:11	Defined based on reporttime timestamp
Testing Period	starts 2024-06-07 02:11	Beginning of the test data window
Mean Absolute Error	27.27 L/h	Average absolute deviation between predicted and actual fuel consumption
Mean Squared Error	1620.08 $(L/h)^2$	Average of squared prediction errors
Root Mean Squared Error	40.25 L/h	Square root of MSE; provides interpretable error in same unit as target
R-squared (R^2)	0.7592	Indicates that the model explains 75.92% of the variance in fuel consumption

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Initial evaluation of the Gradient Boosting Regressor model showed quite good performance in predicting fuel consumption (fuel_rate_01l) based on vehicle behavior and operational features. Based on the test results on the test data, the model produced an MAE value of 27.27 L/h, an MSE of 1,620.08 L/h², and a determination coefficient R^2 of 0.7592. The R^2 value approaching 0.76 indicates that the model is able to explain about 76% of the variation in fuel consumption based on the given input. The MAE and MSE values represent the average prediction error in relevant units (liters per hour), so they can be used as benchmarks in the context of vehicle operational performance. The evaluation process of this model is briefly presented in Table 4. Initial Evaluation of the Gradient Boosting Regressor Model, and the results serve as a reference before applying an adaptive approach designed to handle potential changes in data distribution over time.

3.4. Feature Importance and Model Interpretability Analysis

To further interpret the behavior of the proposed Gradient Boosting Regressor model, SHAP-based analysis was performed to quantify the contribution and directional influence of each predictor on fuel consumption estimation. The global feature contribution patterns and directional effects are presented in Figure 8.

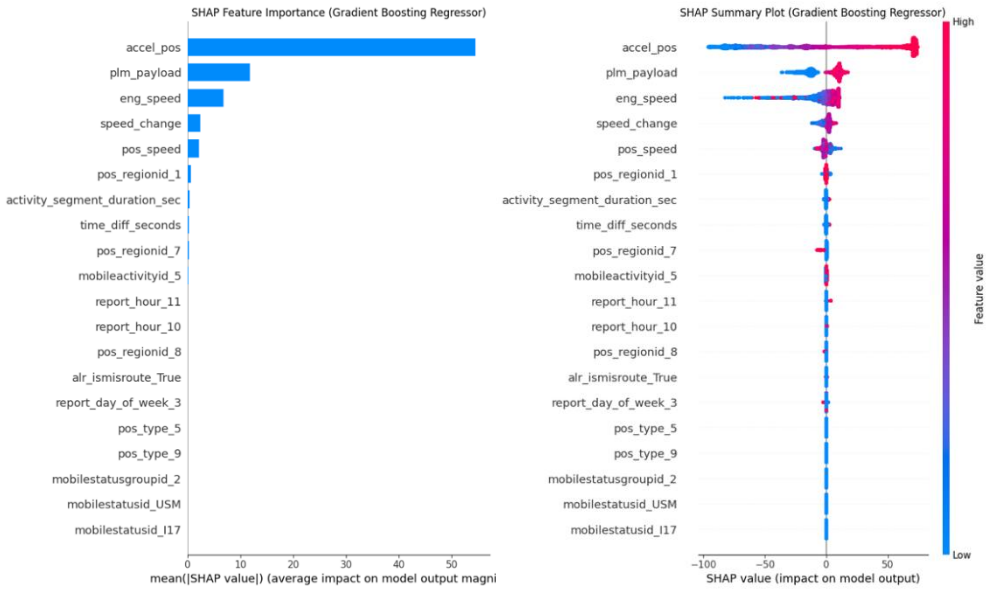

Figure 8. SHAP-based interpretability analysis of the Gradient Boosting Regressor: (a) mean absolute SHAP feature importance; (b) SHAP summary plot.

As shown in Figure 8(a), which illustrates the mean absolute SHAP feature importance, accelerator position (accel_pos) dominates the model's predictive structure, with a substantially higher average impact than all other variables. This indicates that throttle input is the primary determinant of predicted fuel consumption in the observed operational context. The second- and third-most-influential variables are payload (plm_payload) and engine speed (eng_speed), confirming that both load conditions and engine rotational dynamics significantly influence fuel consumption.

Figure 8(b) provides additional insight into the direction and dispersion of feature effects through the SHAP summary plot. The color gradient indicates feature value magnitude, while the horizontal spread represents the impact on model output. For the accelerator position, higher values (represented in red) consistently yield positive SHAP values, indicating increased predicted fuel consumption. Conversely, lower accelerator values contribute negatively to the output. A similar directional trend is observed for payload and engine speed, reinforcing the physical interpretation that higher load and engine activity are associated with higher fuel demand.

Other dynamic variables, such as speed_change and pos_speed, exert a moderate influence, suggesting that transient driving behavior and instantaneous velocity contribute to fuel variability,

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though to a lesser extent than throttle and payload. In contrast, contextual and categorical features, including region identifiers and time-based reporting variables, show minimal SHAP impact, suggesting that short-term fluctuations in fuel consumption are primarily driven by real-time operational dynamics rather than static contextual attributes.

3.5. Concept Drift Detection

To monitor the stability of the model during the test period, concept drift detection based on model performance is performed using a batch-wise performance monitoring approach. In this scenario, we periodically evaluate the Gradient Boosting Regressor model using simulated test data as a data stream.

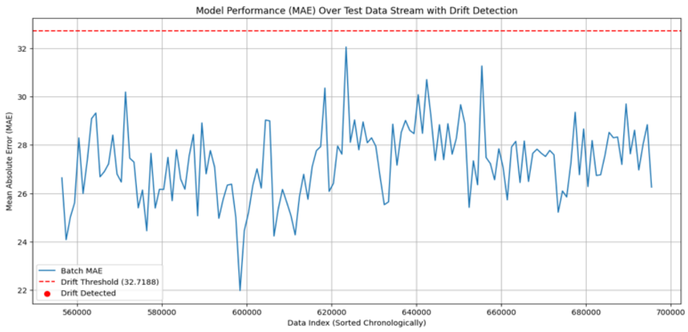

Figure 9. Monitoring MAE for concept drift detection

Using the MAE observation approach per batch, we detected no concept drift throughout the testing period. This assertion is confirmed through the visualization in Figure 9, which shows that the MAE value per batch continues to fluctuate but remains below the drift threshold of 32.7188 L/h. The graph shows that all batch MAE values are consistently below the predetermined threshold, and not a single drift detection point appears during monitoring. Thus, the Gradient Boosting Regressor model shows stable performance and does not experience significant predictive degradation to the dynamics of the test data. These results strengthen the validity of the initial model and demonstrate its resilience to changes in data distribution in the short term. Batch-wise MAE monitoring served as a proxy to indicate performance variations over time. This method functions as an effective performance monitoring drift proxy, especially in real-world systems that favour lightweight implementation.

3.6. Adaptive Learning Implementation Approach

We conducted an adaptive learning approach simulation through periodic retraining to improve the model's resilience to potential performance degradation during long-term use. Figure 10 presents the performance dynamics of the adaptive model against test data sequentially based on the chronological index. The MAE value is calculated for each batch, and the retraining event is marked with a purple triangle symbol. The horizontal green line shows the average initial MAE of the model (27.27 L/h) as a benchmark.

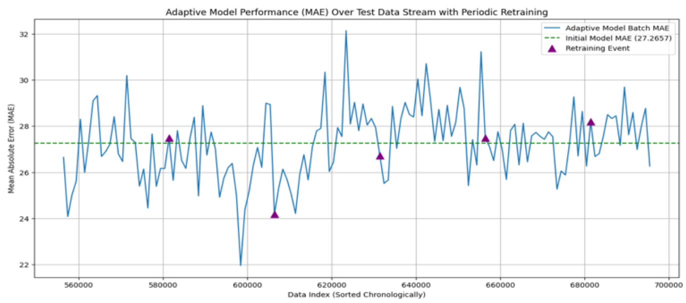

Figure 10. Adaptive learning simulation

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The observed decrease in MAE after the retraining point indicates that periodic model updates help maintain prediction accuracy at a stable level. No significant performance degradation was noted between retrainings, indicating the effectiveness of this adaptive approach in managing operational data fluctuations. This method is advantageous for real-world systems that may experience variations in data patterns over time, although no obvious changes were detected in this case.

Adaptive model performance evaluation is done to check how well the periodic retraining strategy keeps the model's prediction accuracy up to date as data changes over time. Table 5 presents a comparison of evaluation metrics between the baseline and adaptive models.

Table 5. Adaptive Comparison of Initial Model and Adaptive Model Performance

Metric	Initial Model	Adaptive Model
Average Batch MAE	27.2657	27.2327
Overall MAE on Test Data	27.2657	27.1655
Overall MSE on Test Data	1620.0837	1614.4258
R-squared (R^2)	0.7592	0.7600

The comparison results in Table 5 show that the adaptive model provides a slight increase in overall accuracy compared to the initial model. The MAE and MSE values decrease slightly, while the R^2 value increases from 0.7592 to 0.7600. This indicates that the periodic retraining strategy can maintain and even improve the model's ability to explain fuel consumption variability in the test data. The adaptive model method that uses periodic retraining is a good way to keep the accuracy of predictions even when data patterns and the vehicle's operating conditions change.

Although the adaptive retraining strategy yielded only marginal performance improvements over the initial model, this outcome is consistent with the relatively stable characteristics of the evaluated dataset. The telemetry data span approximately one week of operation, during which no significant concept drift was detected based on the predefined threshold. As a result, the baseline model had already captured the dominant behavioral and operational patterns, limiting the potential gain from retraining. This finding indicates that the proposed framework effectively preserves predictive stability under short-term stationary conditions while remaining prepared to adapt to longer-term scenarios in which substantial distributional shifts may occur.

4. DISCUSSION

4.1. Interpretation of Concept Drift Detection Results

Based on monitoring the MAE values per batch during the testing period, the evaluation results reveal no concept drift. All MAE values are consistently below the designated threshold of 32.72 L/h, signifying the model's stable performance in forecasting fuel consumption. The lack of drift may indicate a stable operational environment and consistent driver behavior during the initial observation period of approximately one week. Elements, including routes, vehicle classifications, and consistent load patterns, can influence the stability of data distribution during this timeframe.

The baseline model achieved an R^2 value of 0.7592, demonstrating strong nonlinear modeling capability. This observation aligns with prior findings that ensemble tree-based models are often robust

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to moderate distributional shifts [13]. However, as noted in data stream literature, performance-based monitoring approaches may have limited sensitivity to gradual covariate drift that does not immediately manifest in error escalation, particularly in performance-aware monitoring schemes [20], [35], [36].

4.2. Interpretation of Adaptive Learning Results

Although concept drift was not detected, the adaptive learning approach through periodic retraining resulted in consistent, albeit small, performance improvements. The average MAE decreased from 27.2657 L/h in the baseline model to 27.1655 L/h in the adaptive model, while the R^2 value increased from 0.7592 to 0.7600. These results indicate that scheduled retraining can help maintain or slightly enhance predictive accuracy under streaming conditions. This finding aligns with continual learning principles emphasizing the importance of periodic model updates in systems that process evolving data streams [39].

When compared with recent fuel consumption prediction studies in the heavy-duty and maritime domains, reported MAE values typically range from 25 to 35 L/h, depending on dataset scale and feature richness [25], [40], [41]. However, most of these studies employ static train–test evaluation frameworks that do not integrate adaptive retraining or performance-aware drift monitoring. In contrast, the present study evaluates predictive stability under a streaming simulation setting, incorporating batch-wise monitoring and periodic adaptation.

Deep learning approaches such as LSTM or hybrid CNN–LSTM architectures have demonstrated competitive predictive accuracy in similar domains [42], [43]; however, they typically require higher computational resources and may lack transparent interpretability mechanisms. By combining ensemble regression with SHAP-based interpretability, the proposed framework balances predictive accuracy, robustness, and computational feasibility, which are critical considerations in industrial telemetry and data stream environments. The marginal magnitude of improvement observed in this study is likely attributable to the limited temporal span of the dataset. Under short-term quasi-stationary conditions, retraining primarily reinforces existing patterns rather than restructuring the predictive function. Nevertheless, the adaptive mechanism ensures preparedness for potential long-term shifts in operational regimes and supports stable regression performance in dynamic industrial data streams.

The adaptive model performance also exhibits stabilization following retraining, as illustrated in the batch evaluation plot. This suggests that periodic updates can mitigate the gradual accumulation of bias from outdated data, even in the absence of explicit drift signals [44], thereby maintaining predictive robustness over time.

4.3. Implications for Informatics and Industrial Data Streams

From an informatics standpoint, this study contributes to adaptive regression modeling in high-frequency industrial data stream environments. While much of the concept drift literature focuses on classification problems [35], [45] the present work demonstrates a practical regression-oriented implementation using a relative performance degradation criterion. The integration of threshold-based monitoring with periodic retraining offers a computationally lightweight alternative to statistically intensive drift-detection algorithms.

Such lightweight adaptive strategies are particularly relevant for industrial IoT and edge computing environments, where bandwidth and computational resources may be constrained [46]. In mining operations and other telemetry-intensive domains, continuous streaming data require monitoring mechanisms that are both interpretable and resource-efficient. The proposed framework illustrates that effective adaptation can be achieved without complex online learning architectures, thereby broadening the applicability of adaptive regression techniques beyond laboratory-scale experimentation.

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Moreover, the methodological design combining structured behavioral–operational feature taxonomy, SHAP-based interpretability, and batch-wise performance monitoring can be extended to other high-frequency sensor applications, including maritime propulsion systems, fleet telematics, and industrial equipment diagnostics.

5. CONCLUSION

This study developed an adaptive machine learning framework for fuel consumption prediction in mining haul trucks using high-frequency telematics data. The proposed framework integrates structured behavioral and operational feature identification, a Gradient Boosting Regressor–based prediction model, and a performance-aware monitoring mechanism combined with periodic retraining under streaming data conditions.

The findings demonstrate that the selected behavioral and operational indicators effectively capture the dominant patterns governing fuel consumption, and batch-wise monitoring confirms the model's stability during the observed period. Although no significant concept drift was detected, periodic retraining helped maintain predictive robustness and prevent potential performance degradation. These results indicate that adaptive updates can serve as a proactive stabilization strategy even in relatively stationary environments. From an informatics perspective, this work contributes to the development of lightweight adaptive regression systems for high-frequency industrial data streams. By employing a relative performance degradation criterion rather than computationally intensive statistical drift detectors, the proposed framework offers a practical, resource-efficient solution suitable for edge or IoT-based deployment in industrial settings with limited bandwidth and computational capacity.

Future research should extend the temporal scope of data collection to evaluate long-term non-stationary behavior across multiple operational sites. The integration of formal drift detection algorithms, such as adaptive window-based or error-rate-based detectors, and the exploration of online or ensemble-based adaptive learning strategies may further enhance sensitivity to gradual and abrupt distributional shifts.

CONFLICT OF INTEREST

The authors declare that they have no competing interests or financial conflicts that could have influenced the outcomes of this study.

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