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Real-Time Explainable Concept Drift Detection for Eco-Driving in Mining Trucks using KSWIN and Event-Triggered SHAP

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Abstract. Fuel consumption represents a significant operational cost in mining, where real-time eco-driving optimization is hindered by dynamic and non-stationary operating conditions. Variations in operator behavior and environmental factors often induce concept drift, which diminishes the reliability of static machine learning models and constrains the effectiveness of conventional drift detection methods. This study proposes a distribution-aware, event-triggered Explainable Artificial Intelligence (XAI) framework for detecting and diagnosing fuel consumption anomalies in streaming telematics data. A Hoeffding Tree Regressor was evaluated using a prequential scheme on 1,927,867 real-world observations, achieving a Mean Absolute Error (MAE) of 19.43 under non-stationary conditions. Concept drift was monitored using the Kolmogorov–Smirnov Windowing (KSWIN) algorithm, which detected 1,874 drift events. Upon detection, an event-triggered SHAP module identified contributing factors, indicating that behavioral features such as engine speed and accelerator position were dominant contributors in early drift events. The primary contribution of this study is the integration of distribution-based drift detection with event-triggered explainability within a unified streaming framework, facilitating both anomaly detection and interpretable root-cause analysis.

Keywords: Online Learning, Concept Drift, Explainable AI, Prequential Learning, KSWIN, SHAP Attribution, Eco-Driving, Heavy Equipment Telematics

1. INTRODUCTION

Fuel consumption is one of the most significant components of operational expenses in the open-pit mining industry. Implementing eco-driving practices and payload management is crucial for cost efficiency and environmental impact mitigation [1], [2]. Operator behavior while driving, such as engine speed management and acceleration, interacts complexly with external factors such as road gradient and load to influence fleet efficiency [2], [3]. Historically, heavy equipment fuel consumption modeling has relied heavily on conventional statistical models or batch-based machine learning [4]. A recent systematic review shows that although adaptive machine learning approaches to fuel efficiency optimization have evolved, most research still focuses on static or semi-adaptive predictive models and has not explicitly integrated operator behavior analysis in a real-time streaming framework [5]. However, these static approaches have a fatal flaw when applied to real-life mining areas, the models are unable to adapt to mechanical degradation or changes in road topography in real time, resulting in a sharp decline in accuracy over operational time [6], [7].

With the massive adoption of the Internet of Things and sensors, modern dump truck fleets now generate high-speed telemetry data streams, opening up opportunities for real-time analytics [7]. Unfortunately, dynamic operational environments often trigger concept drift, namely hidden changes in the statistical distribution of data streams that undermine the accuracy of predictive models [8], [9]. To overcome this, the online machine learning (OML) paradigm has been adopted, enabling the system to learn incrementally [10]. Several studies have proposed drift detectors, such as Adaptive Windowing (ADWIN), that monitor the mean-error rate threshold [7], [11]. However, these conventional detectors often fail to capture more subtle behavioral shifts (gradual drift), such as fluctuations in the operator's accelerator pedal pressure [12], [13]. As an advanced alternative, Kolmogorov-Smirnov Windowing (KSWIN) has been empirically shown to be more sensitive because it monitors changes in the probability distribution [14]. Previous research on eco-driving analytics, concept drift detection, and explainable artificial intelligence has typically examined these areas in isolation, with few studies integrating them into a unified streaming analytical framework for industrial telemetry systems. Although recent work has addressed adaptive learning, concept drift detection, and explainable models in dynamic data environments [6] - [12], their combined application to telemetry analytics remains underexplored. Eco-driving analytics, concept drift detection, and explainable AI are not isolated research directions; instead, they are fundamentally interconnected within real-world industrial telemetry systems, where dynamic operational conditions necessitate concurrent adaptation, detection, and interpretation.

The biggest unresolved challenge after drift detection is algorithm transparency. When an OML model detects an anomaly or performance degradation, the system still operates as a black box, unable to explain the root cause of the drift [15]. The algorithm's inability to distinguish between fuel wastage caused by operator error (behavioral factors) and by terrain constraints (environmental factors) often leads to evaluation bias and misguided managerial decisions [1], [16]. On the other hand, the literature on Explainable Artificial Intelligence (XAI), such as SHAP and LIME, has been growing to open this "black box" [17]. However, most current XAI architectures are still designed exclusively for post-hoc processing of static datasets, making them computationally intensive and unable to provide real-time explanations for data streams [18], [19].

To address this research gap, this study introduces a real-time analytical framework for explainable concept drift detection in mining truck eco-driving telemetry streams. In contrast to traditional methods, the framework integrates prequential learning, distribution-based drift detection using the Kolmogorov–Smirnov Windowing (KSWIN) algorithm, and an event-triggered SHAP explainability mechanism to analyze streaming operational data [20], [21]. This event-triggered mechanism enables the system to decouple feature attribution from classification of the root cause of detected drift as either behavioural or environmental drift in near real time [19].

The primary contributions of this study are as follows. First, it presents an integrated streaming analytical framework that combines online predictive modeling with distribution-based drift detection for mining telemetry data. Second, it introduces an event-triggered explainability mechanism that activates SHAP attribution exclusively when statistically significant drift events are detected. Third, it offers an interpretable root-cause classification strategy that distinguishes operator behavioral effects from environmental operating conditions in eco-driving analysis. By integrating drift detection with explainable attribution in a streaming context, the proposed framework advances research in industrial data stream analytics. It facilitates more transparent operational monitoring of heavy equipment systems.

2. METHODS

The proposed methodological framework enables real-time detection and explanation of concept drift within telemetry data streams. This framework incorporates streaming data ingestion, feature decoupling, prequential predictive modeling, distribution-based concept drift detection using the Kolmogorov–Smirnov Windowing (KSWIN) algorithm, and an event-triggered SHAP explainability module. As shown in Figure 1, the analytical pipeline proceeds sequentially: it begins with telemetry data ingestion and feature preparation, continues with online prediction and error monitoring, applies drift detection using KSWIN, and concludes with root-cause interpretation through SHAP-based attribution.

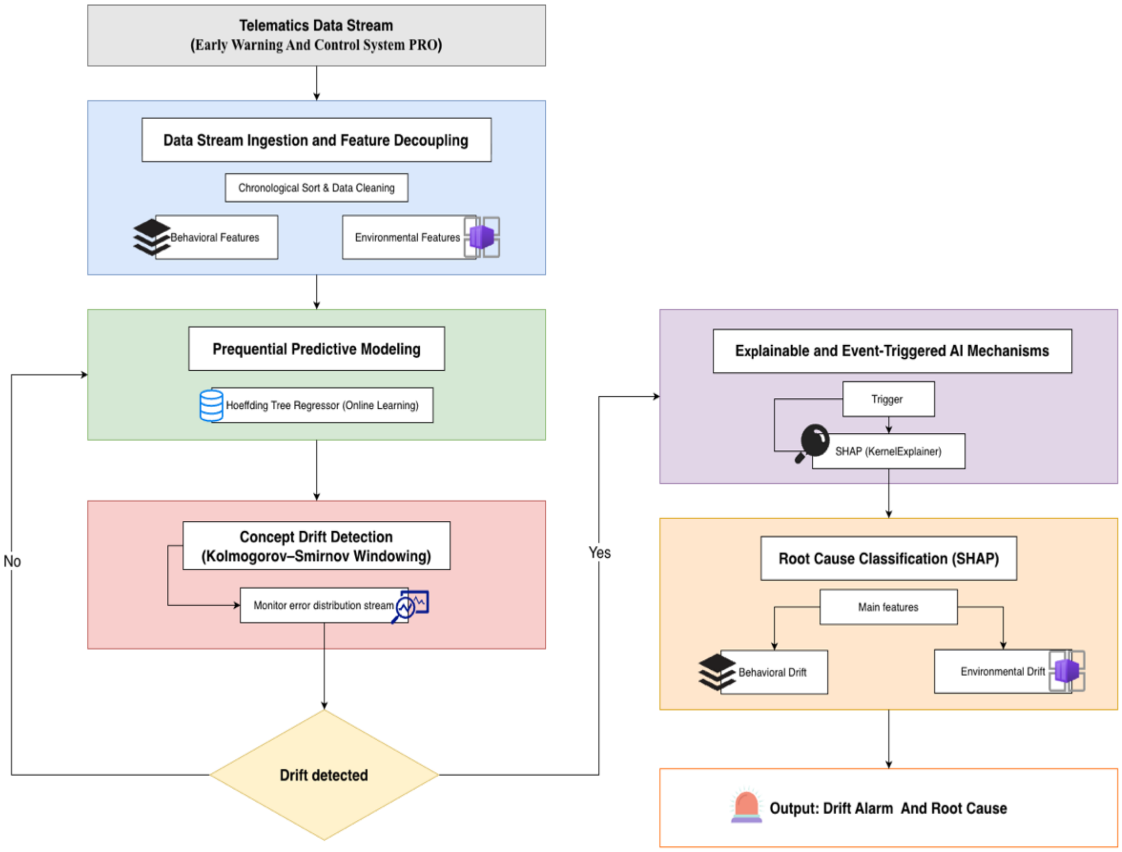

Figure 1. Workflow of the proposed real-time explainable concept drift detection framework

2.1. Data Stream Ingestion and Feature Decoupling

The telematics system in a mining dump truck fleet produces high-frequency, continuous, and non-stationary operational data streams. In the context of online learning, incoming telemetry is processed sequentially as a temporally ordered stream of observations. At each time step t, the data stream is represented as an observation pair (x_t, y_t), where $x_t \in \mathbb{R}^d$ denotes a d-dimensional feature vector and $y_t \in \mathbb{R}$ represents the target variable observed at that time.

The target variable y_t in this study is defined as the absolute fuel consumption rate (fuel_rate_01l). This variable was selected due to its direct relationship with operational efficiency and the environmental impact of mining haulage activities. By continuously monitoring changes in this variable, the system can detect performance degradation and abnormal driving behavior at an early stage.

To support the implementation of explainable concept drift detection and root cause analysis, the input feature vector x_t is explicitly separated into two semantically independent feature subspaces:

$$x_t = X_{beh,t} \cup X_{env,t} \tag{1}$$

where:

$X_{beh,t}$ (behavioral features) represent variables directly influenced by operator decisions, including engine speed (eng_speed), accelerator pedal position (accel_pos), foot brake position (foot_brake_pos), and gear shift indicator (shift_indicator).

$X_{env,t}$ (environmental features) represents physical conditions and operational context beyond the operator's direct control, including payload weight (plm_payload), road gradient (plm_inc), and geographic altitude (pos_alt).

The feature-separation strategy offers a structured representation of operational telemetry data and facilitates differential attribution of concept drift events. By distinguishing between behavioral and environmental variables, the analytical framework identifies whether variations in fuel consumption are primarily linked to operator driving behavior or to external operating conditions.

Prior to the streaming data simulation, the dataset is chronologically ordered based on the time attribute (reporttime) to ensure temporal consistency. Chronological ordering is critical in prequential learning environments, as the sequence of observations directly affects model updates and drift sensitivity. Missing feature values are addressed using forward propagation (forward filling) to approximate real-time telemetry availability in operational contexts.

2.2. Prequential Predictive Modeling

Unlike traditional batch learning approaches that assume a static data distribution, this study applies a prequential evaluation paradigm (interleaved test-then-train) to model fuel consumption in a non-stationary data stream scenario [22], [23]. This paradigm is specifically designed for online learning, where observations are processed sequentially according to their temporal order.

At each time point t, the online regression model H_t first generates a fuel consumption prediction based on the available features:

$$\hat{y}_t = H_t(x_t) \tag{2}$$

The prediction is performed before the system receives the actual value of y_t, thus reflecting real-time inference conditions without information leakage. Once the exact value is available, the system calculates the absolute error:

$$e_t = | y_t - \hat{y}_t | \tag{3}$$

These error values are accumulated using the Mean Absolute Error (MAE) metric to indicate the model's global performance across the data stream. Additionally, the error time series e_t is used as the primary signal for the concept drift detection stage, as is common in model performance-based drift approaches. The model is then incrementally updated using the most recent observations:

$$H_{t+1} = \text{Update}(H_t, x_t, y_t) \tag{4}$$

The model used is the Hoeffding Tree Regressor, a decision tree algorithm for data streams that utilizes the Hoeffding bound to determine node separation based on sufficient statistical evidence [24]. This approach allows incremental construction of the tree structure with constant memory usage and low computational complexity, making it suitable for large-scale real-time systems.

2.3. Distribution-Based Concept Drift Detection Using KSWIN

To capture changes in eco-driving behavior, which are often gradual and not always reflected as spikes in the average prediction error, this study detects drift based on shifts in the probability distribution of the prediction error signal e_t, rather than relying solely on average error monitoring. The prediction error is defined as $e_t = | y_t - \hat{y}_t$, where y_t denotes the observed fuel consumption and $\hat{y}_t$ represents the model prediction obtained from the prequential evaluation scheme. Monitoring the error distribution allows the system to capture structural changes in the relationship between operational features and fuel consumption over time.

Kolmogorov–Smirnov Windowing (KSWIN) is a drift detection algorithm based on the nonparametric Kolmogorov–Smirnov (KS) test. It compares two samples from different segments of a sliding window [25], [26]. KSWIN maintains a window of recent prediction errors and evaluates whether the distribution of the newest observations differs significantly from earlier observations. Operationally, KSWIN maintains a sliding window of size N (window_size) representing the recent history of the prediction error stream. From this window, two subsets are sampled: a historical subset and a recent subset, each of size n (stat_size), which are then compared using the KS statistical test.

Let W_{hist} denote the historical error sample and W_{rec} denote the recent error sample. The Kolmogorov–Smirnov statistic is defined as the maximum distance between the empirical cumulative distribution functions (empirical CDFs) of the two samples:

$$D = \sup_{e} | F_{rec}(e) - F_{hist}(e) | \tag{5}$$

where F_{rec} dan F_{hist} denote the empirical cumulative distribution functions of the recent and historical samples, respectively. If the resulting statistic yields a p-value smaller than the predefined significance level α, the null hypothesis H_0 that both samples originate from the same distribution is rejected. In this case, the system declares a concept drift event at time t_{drift}. This distribution-based detection mechanism enables the framework to identify behavioral shifts in eco-driving patterns that may not be detectable through simple error-threshold monitoring.

In the implementation, KSWIN is configured with α=0.01, window_size = 500, and stat_size = 100. The significance level α controls the detector's sensitivity, while the window parameters determine the balance between detection responsiveness and statistical stability. These parameter values are defined as fixed heuristic settings based on preliminary experimentation, intended to balance detection sensitivity and computational stability rather than representing globally optimal configurations. The detected drift indices are recorded as candidate change points and subsequently used to trigger the explainability module, enabling root-cause analysis of the operational conditions associated with each drift event.

2.4. Event-Triggered Explainable AI Mechanism

The subsequent stage of the analytical pipeline incorporates an event-triggered Explainable Artificial Intelligence (XAI) mechanism to interpret the root causes of detected drift events. Unlike conventional post-hoc explainability approaches that analyze the entire dataset, the SHAP-based explanation process employed in this study is activated exclusively when the KSWIN detector signals a drift event at time $t = t_{\text{drift}}$. This event-triggered strategy substantially reduces computational overhead in streaming environments and ensures that explainability analysis targets operationally significant behavioral changes.

Upon triggering a drift alarm, the system isolates a subset of historical observations preceding the drift point to serve as the local explanatory context. In this study, a window of 150 observations centered on the detected drift point is employed to represent the system's operational state prior to the distribution shift. The most recent 10 observations associated with the drift alarm are subsequently analyzed to identify the immediate behavioral patterns contributing to the detected drift. The 150-observation contextual window was chosen to balance comprehensive historical representation of the operational state with computational feasibility for real-time explanation. The final 10 observations represent the most recent behavioral patterns responsible for triggering the drift detection signal. These parameters were established as fixed heuristic values following preliminary experimentation with large-scale telemetry streams.

To generate model-agnostic explanations of the predictive model, the KernelExplainer implementation of the SHapley Additive exPlanations (SHAP) method is employed. SHAP explains individual predictions by attributing contributions to each feature using the Shapley value concept from cooperative game theory. The Shapley value ϕ_i for the i-th feature is computed as the average marginal contribution of that feature across all possible feature subsets:

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N|-|S|-1)!}{|N|!} [v(S \cup \{i\}) - v(S)] \tag{6}$$

where N is the set of all features, S is a subset of the features, and $v(S)$ is the model's predicted output for that subset. The ϕ_i value represents the contribution of each feature to the deviation of the expected fuel consumption during the drift period.

Evaluating feature attributions within a localized temporal context allows the framework to identify operational factors that contribute to distributional shifts in the prediction error stream in an interpretable manner. The current implementation, however, relies on deterministic attribution ranking and does not explicitly account for uncertainty or mixed-cause drift scenarios. These limitations may be addressed in future extensions of the framework.

2.5. Root Cause Classification Based on SHAP Attribution

After the Shapley values are calculated, the system aggregates the average absolute values of $|\phi_i|$ to determine the features that most dominantly influence the prediction during the drift period.

Referring to the semantic separation of features in the feature decoupling results, the system applies deterministic inference rules to classify the drift type as follows:
If

$$max\ (|\ \phi_{X_{beh}}\ |) > max\ (|\ \phi_{X_{env}}\ |) \tag{7}$$

Then the drift is classified as behavioral drift, indicating that changes in fuel consumption are primarily triggered by changes in operator behavior, such as engine speed spikes or aggressive acceleration.

Conversely, if

$$\max(|\phi_{X_{env}}|) > \max(|\phi_{X_{beh}}|) \tag{8}$$

Then the drift is classified as environmental drift, indicating that the increase in fuel consumption is predominantly influenced by external conditions such as load or terrain gradient. This approach allows the system not only to detect distribution changes but also to explicitly identify the operational sources of these changes in an actionable manner.

The deterministic attribution rule was intentionally developed to maintain interpretability in operational monitoring systems, enabling domain experts to directly associate drift events with dominant behavioral or environmental factors. However, this rule-based classification does not explicitly account for uncertainty or mixed-cause drift scenarios in which both feature groups contribute simultaneously. Subsequent research could investigate probabilistic or hybrid attribution strategies to better capture complex causal interactions within streaming telemetry environments.

3. RESULTS AND DISCUSSION

3.1. Experiment Setup and Dataset

The experiment was conducted using a real-world operational dataset from a telematics system for a dump truck fleet in an open-pit mining environment. This dataset was collected continuously during daily operations and processed as a sequential data stream. After cleaning and chronological sorting by the time attribute (reporttime), 1,927,867 observations were obtained, ready for processing using the online learning scheme. A summary of the dataset configuration and experimental architecture is shown in Table 1.

Table 1. Summary of Dataset and Feature Configuration

Component	**Description**
Total Observations	1,927,867
Data Type	Real-world telematics data stream

Component	Description
Target Variable	fuel_rate_01l (Absolute Fuel Consumption)
Learning Paradigm	Prequential (Interleaved Test-Then-Train)
Behavioral Features (X_beh)	accel_pos, foot_brake_pos, eng_speed, shift_indicator
Environmental Features (X_env)	plm_payload, plm_inc, pos_alt
Drift Detector	KSWIN (α = 0.01, window_size = 500)
XAI Method	SHAP (KernelExplainer, event-triggered)

The predicted target variable is the absolute fuel consumption rate (fuel_rate_01l). The predictor features are separated into two subspaces, namely, behavioral features (eng_speed, accel_pos, foot_brake_pos, shift_indicator) and environmental features (plm_payload, plm_inc, pos_alt). This explicit feature separation is crucial to facilitate root cause classification in the XAI stage, a specific approach that has not been widely adopted in conventional data stream architectures [19].

3.2. Evaluation of Prequential Predictions and Limitations of the Static Model

The Hoeffding Tree Regressor model was evaluated using the Interleaved Test-Then-Train method. Experimental results showed that the model produced a Mean Absolute Error (MAE) of 19.43, indicating the average absolute error in fuel consumption predictions relative to actual values.

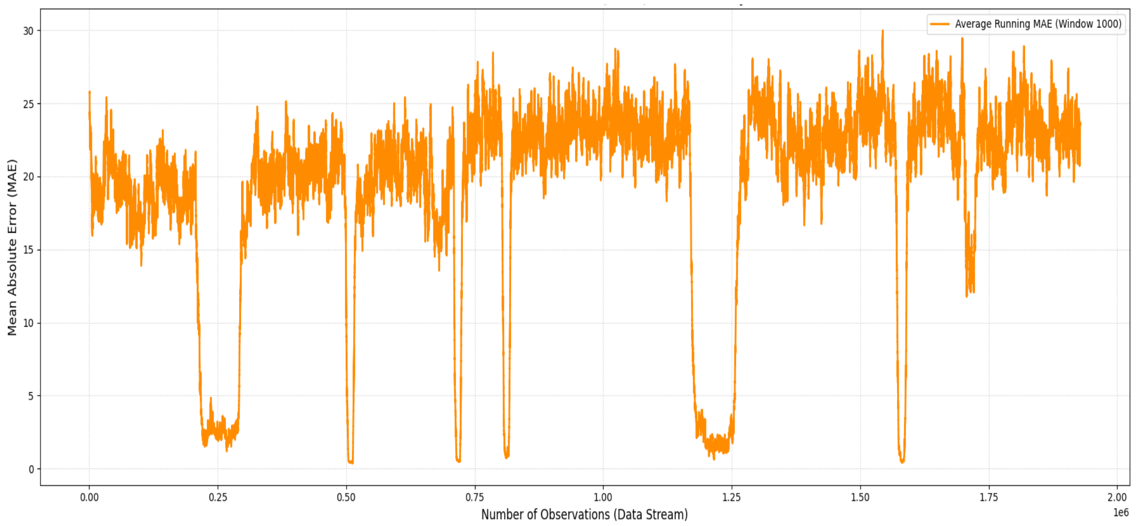

Figure 2. Evolution of MAE in Prequential Evaluation

As shown in Figure 2, the MAE evolution shows inconsistent performance dynamics. In the initial phase, the MAE is relatively high, but gradually improves as the incremental learning process continues. Peak performance is achieved around the 295,000th observation, with an MAE of 14.5230, indicating that the model learns the initial pattern of the relationship between operational features and fuel consumption. However, after that point, the MAE value gradually increases again, reaching around 19.43 at the end of the data stream. This gradual increase indicates performance degradation due to changes in data distribution, a common phenomenon in predictive systems operating in non-stationary environments and industrial IoT systems [8], [27], [28]. In addition to the gradual trend, the MAE graph also shows several segments of sharp declines to very low values. Operationally, this phenomenon indicates a change in operating regime (e.g., a period of very stable operating conditions or a target value close to zero), thereby making the prediction model more reliable over specific intervals. Since this research focuses on real-world data streams, the presence of such regimes is expected and reflects the complex and evolving operational dynamics of mining environments.

This finding has important implications, although Hoeffding Trees can learn incrementally, learning mechanisms alone are not always sufficient to maintain long-term performance when data patterns shift. The data stream literature emphasizes that under non-stationary conditions, predictive systems require drift detection and/or adaptation strategies (e.g., partial resets, adaptive retraining, or weighting recent data) to prevent error accumulation [27], [28]. In the context of mining vehicle fuel consumption modeling, previous studies have also shown that consumption is simultaneously influenced by driver behavior, load, and route/terrain conditions, so that changes in operating conditions can alter the feature-target relationship [29], [30]. Therefore, the gradual increase in MAE in this experiment reinforces the need for a concept drift detection module as a mandatory component, not an optional feature.

3.3. Distribution-Based Concept Drift Detection

The prediction error distribution was monitored using the Kolmogorov–Smirnov Windowing (KSWIN) algorithm on the absolute error time series generated from the prequential evaluation. Out of a total of 1,927,867 observations, the KSWIN detector identified 1,874 Concept Drift events, which roughly equate to approximately one distribution shift per 1,029 observations.

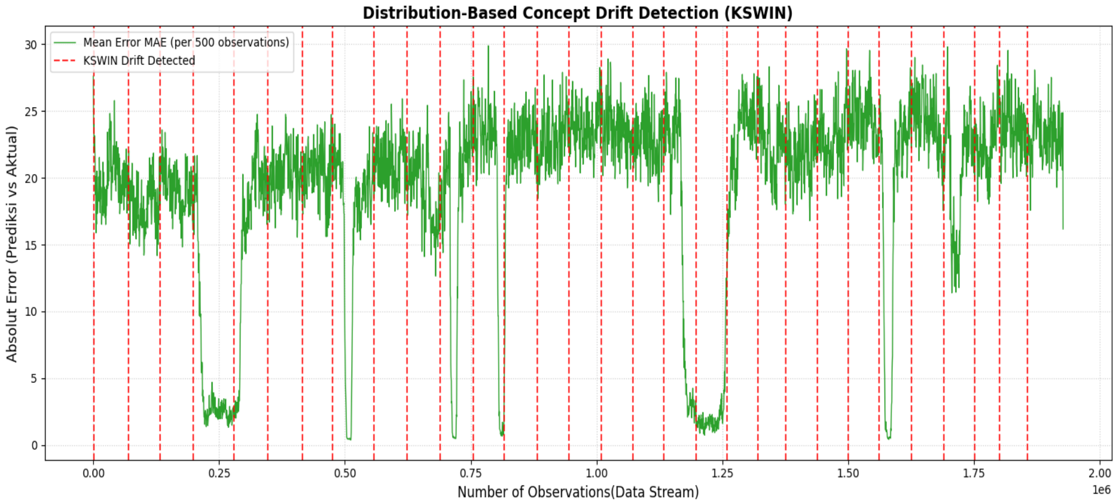

Figure 3. Distribution-Based Concept Drift Detection Using KSWIN on Prequential Error Time Series

As shown in Figure 3, the red vertical lines indicate the time points at which the Kolmogorov–Smirnov test rejects the null hypothesis that the historical and current error distributions are identical. The first five drift points were detected at indices (499, 1217, 1777, 2390, 2916), indicating that distribution nonstationarity emerged early in the data stream.

The relatively high drift frequency reflects the dynamic nature of mining operational environments. However, it may also partially result from the detector configuration's sensitivity, which is designed to capture subtle distributional shifts in large-scale streaming data. Variations in load, changes in road gradients, mine surface conditions, and operator behavior over time contribute to fluctuations in the distribution of prediction errors. This phenomenon is consistent with data stream literature, which states that real-world systems rarely meet the assumption of a static distribution over the long term [31].

In contrast to approaches based on the mean error threshold, KSWIN monitors shifts in the overall probability distribution, including changes in its variance and shape. This is important because in many operational situations, drift does not necessarily manifest itself as a sharp spike in the mean error, but rather as a gradual change in the pattern of variability. Distribution-based approaches like KSWIN are theoretically more sensitive to this type of gradual drift than methods based solely on mean comparison [32].

The large number of drifts (1,874 points) also indicates that the detector's sensitivity ($\alpha = 0.01$; window_size = 500; stat_size = 100) significantly affects the alarm frequency. In practice, very high alarm frequencies may render monitoring systems practically useless. Therefore, these results simultaneously confirm that deviation detection cannot stand alone, but requires an interpretability mechanism to determine whether the deviation has operational relevance. Thus, the results of this experiment provide two main findings: first, dump truck fuel consumption data is statistically non-stationary, and second, the distribution-based approach effectively captures subtle changes that are not always reflected in the average MAE.

3.4. Root Cause Analysis with Explainable AI

To enhance model transparency and identify the operational causes of detected distribution shifts, the SHAP-based Explainable AI module is reactively activated at the first detected drift event (drift index 499). This event-triggered mechanism ensures that feature attribution is computed only when the KSWIN detector signals a statistically significant change in the distribution of the prediction error. By limiting SHAP computation to drift moments, the framework maintains computational efficiency while concentrating interpretability analysis on operationally critical events.

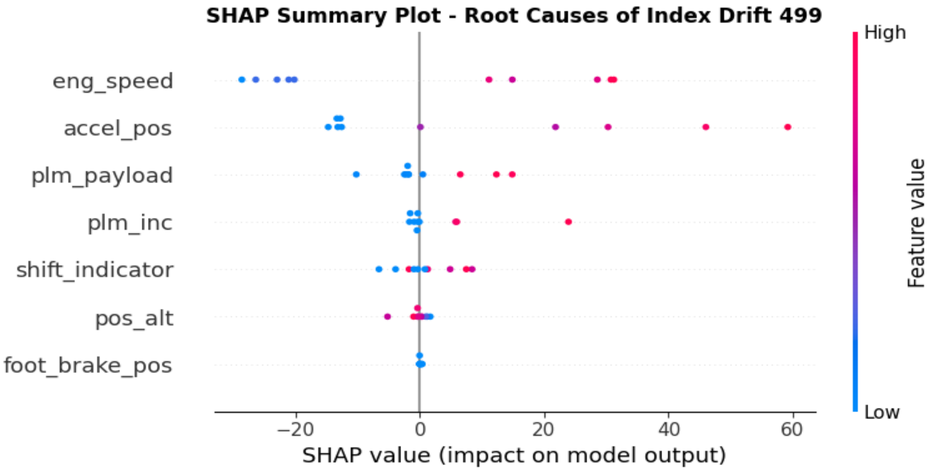

Figure 4. SHAP Summary Plot for Root Cause Analysis at the First Drift Point

As illustrated in Figure 4, behavioral variables clearly dominate the SHAP attribution spectrum at the first drift event. The feature eng_speed exhibits the highest average absolute SHAP magnitude (≈24.75), followed closely by accel_pos (≈22.09). The distribution of SHAP values shows strong positive contributions for higher engine speeds and more aggressive accelerator usage, indicating that these factors significantly increase predicted fuel consumption during the drift period.

In contrast, environmental variables such as plm_payload (≈6.27), plm_inc (≈3.71), and pos_alt (≈1.39) demonstrate comparatively lower attribution magnitudes. Although they contribute to model output, their influence remains substantially lower than that of the leading behavioral features. This attribution pattern indicates that the detected distribution shift at drift index 499 is primarily associated with changes in operator driving behavior rather than environmental or terrain-related factors. To ensure that these results are not a local phenomenon at one drift point, a comparative analysis was performed on the first five drift points as summarized in Table 2.

Table 2. Full SHAP Attribution Comparison for Five Initial Drift Events

Drift Index	**Top Contributing Feature**	**Root Cause**	**SHAP Attribution Ranking (Descending)**
499	eng_speed	Behavioral Drift	eng_speed (24.75) > accel_pos (22.09) > plm_payload (6.27) > shift_indicator (5.24) > plm_inc (3.71) > pos_alt (1.39) > foot_brake_pos (0.10)
1217	eng_speed	Behavioral Drift	eng_speed (32.61) > accel_pos (22.59) > shift_indicator (7.65) > plm_payload (7.07) > plm_inc (2.23) > pos_alt (0.74) > foot_brake_pos (0.10)
1777	accel_pos	Behavioral Drift	accel_pos (28.99) > eng_speed (18.43) > plm_payload (6.55) > shift_indicator (6.37) > plm_inc (3.56) > pos_alt (1.28) > foot_brake_pos (0.17)
2390	accel_pos	Behavioral Drift	accel_pos (33.48) > eng_speed (26.60) > plm_payload (7.80) > shift_indicator (6.52) > plm_inc (3.10) > pos_alt (2.40) > foot_brake_pos (0.24)
2916	accel_pos	Behavioral Drift	accel_pos (26.88) > eng_speed (23.62) > plm_payload (8.97) > shift_indicator (7.60) > pos_alt (1.90) > plm_inc (0.95) > foot_brake_pos (0.00)

As presented in Table 2, behavioral features consistently dominate the SHAP attribution rankings across all five initial drift events. At drift indices 499 and 1217, eng_speed emerges as the top contributing feature, while at indices 1777, 2390, and 2916, accel_pos becomes the most influential variable. In every case, the highest absolute SHAP values are attributed to behavioral features, indicating that variations in engine speed and accelerator usage have the greatest impact on the model output during drift periods. Although the detailed attribution analysis focuses on the first five drift events for interpretability, these early events provide representative insights into the dominant behavioral patterns observed throughout the streaming data.

Environmental variables such as plm_payload, plm_inc, and pos_alt do contribute to the prediction; however, their SHAP magnitudes remain consistently lower than those of the leading behavioral variables. Even when environmental contributions increase (e.g., plm_payload reaching 8.97 at index 2916), they do not surpass the dominant behavioural effects. This consistent dominance of behavioral features across multiple drift points confirms that the early-phase drifts in the data stream are systematically classified as behavioral drift, rather than environmentally driven distributional changes.

Based on the inference rules defined in the methodology phase, which compare the maximum absolute attribution values between the behavioral and environmental feature subspaces, this drift event was therefore classified as behavioral drift. In other words, the spike in fuel consumption during this period was predominantly caused by changes in the operator's driving pattern rather than external factors such as load or road gradient. These results are consistent with the eco-driving literature, which states that engine speed and acceleration intensity are the primary determinants of fuel inefficiency in heavy vehicles [29], [33].

Furthermore, this approach extends the implementation of Explainable AI in industrial data stream systems. Unlike conventional post-hoc approaches that perform interpretability analysis after the entire operational cycle is complete, this framework demonstrates that feature attribution can be performed prescriptively and in near real-time when drift is detected. The integration of KSWIN-based distribution detection and SHAP attribution analysis enables the system not only to detect that a change has occurred but also to explain why it occurred. The practical implications are significant, as the system is able to objectively distinguish between behavioral and environmental factors, thus helping operational management avoid attribution bias when evaluating operator performance. Such interpretability can support more targeted operational interventions, for example by identifying driving patterns that require behavioral coaching rather than mechanical or environmental adjustments.

3.5. Discussion

Experimental results show that the combination of prequential modeling, distribution-based drift detection, and SHAP attribution analysis forms a complementary framework for monitoring fuel consumption dynamics in dump truck fleets [20]. The prequential evaluation phase indicated that although the Hoeffding Tree model is capable of incremental learning, its performance still degrades gradually due to data nonstationarity [9]. This finding confirms that online learning alone is insufficient without a mechanism for monitoring distribution changes [7], [11] .

The implementation of KSWIN on error time series demonstrates that the mining operational environment is highly dynamic, with 1,874 drift points detected throughout the observation period [12], [20]. This reinforces the assumption that sensor-based industrial systems cannot be assumed to follow a fixed distribution in the long term [10]. However, drift detection alone does not provide operational value without an explanation of the source of the change [19].

Explainable AI plays a crucial role. SHAP analysis of the first drift point and subsequent early drift events shows that the error spike is predominantly driven by behavioral features (eng_speed and accel_pos) rather than environmental factors [17]. The integration of drift detection and feature attribution enables the system to answer not only when the change occurred but also how it occurred [29], [34]. The observed predominance of behavioral features may partially result from the deterministic structure of the attribution rule, which prioritizes maximum SHAP magnitude and does not explicitly account for uncertainty or feature interaction effects. Consequently, the system transitions from a monitoring mechanism to an evidence-based diagnostic tool.

From a practical perspective, this approach has direct implications for mining operations management [6]. First, automatically distinguishing between behavioral and environmental drift helps reduce bias in operator performance evaluations. Second, the event-triggered XAI mechanism avoids excessive computational overhead, making it feasible for implementation in large-scale real-time monitoring systems. Third, the resulting root cause information can be used as the basis for prescriptive interventions, such as operator retraining, operational policy adjustments, or vehicle technical inspections [15], [16], [32].

Methodologically, these findings demonstrate that an integrated architecture incorporating incremental learning, distribution-based drift detection, and game-theory-based interpretability offers a more robust and adaptive solution for managing non-stationary industrial environments than static predictive approaches. Additionally, the proposed framework provides a systematic approach for monitoring fuel consumption dynamics and establishes a transparent basis for data-driven operational decision-making in dynamic mining contexts, aligning with previous research that highlights the importance of intelligent information systems in supporting data-driven analytics and decision-making [35].

4. CONCLUSION

This study proposes an integrated framework for real-time concept drift detection and root-cause analysis in a dump truck fuel consumption monitoring system within a mining environment. Unlike static predictive approaches, the developed method combines prequential incremental learning (Hoeffding Tree Regressor), Kolmogorov–Smirnov Windowing (KSWIN)-based distribution drift detection, and an event-triggered SHAP-based Explainable AI mechanism. Evaluation of real-world telemetry data observations shows that the model produces an overall MAE of 19.43, with performance dynamics reflecting the non-stationary nature of the operational environment. The KSWIN detector successfully identified 1,874 concept drift points, confirming that the prediction error distribution changed significantly throughout the observation period. SHAP attribution analysis at the first drift point revealed that the fuel consumption spike was predominantly triggered by operator behavior factors (eng_speed and accel_pos) rather than environmental factors, thus classified as behavioral drift. The main contribution of this study is to integrate distribution-based drift detection with event-triggered interpretability within a unified data stream monitoring framework. This approach not only detects when distributional changes occur but also provides interpretable insights into their underlying causes, enabling more transparent monitoring of eco-driving behavior. As a future research direction, the evaluation could be expanded by comparing different drift detection methods, adaptively optimizing detector parameters, and testing the system in multi-fleet scenarios or longer operational periods. The integration of automated response mechanisms to detected drift also represents a promising direction toward more adaptive monitoring systems in future research.

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