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Machine Learning-Based Stick-Slip Detection Using Surface Drilling Data

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ABSTRACT

Stick-slip vibration is one of the largest causes of drill bit wear, tool failure and less drilling efficiency during rotary drilling activities. Though they are effective in detecting the downhole vibrations, they are expensive and not always available in drilling campaigns. The study introduces a complete package of stick-slip detection using only the measurements of the surface, torque and rotary speed (RPM), without relying on the expensive downhole sensors. This methodology uses the supervised machine learning classification models that are trained using labelled surface data to differentiate between stick-slip and normal drilling. An artificial dataset with a calibration to drilling activities at the North Sea was created, consisting of 172800 samples (48 hours at 1 Hz) where 15 injected stick-slip events involving torsional oscillations (0.15-0.45 Hz) were characteristic of the databank. There were 21 time-domain and frequency-domain features per 60-second window in feature extraction; comprising the statistical moments, spectral energy in torsional bands (0.1-0.5 Hz) and dominant frequency content. The training and testing of three supervised classifiers, including Logistic Regression, Support Vector Machine (SVM) and Random Forest were systematically trained and tested with stratified 80-20 train-test splits. The three models were found to perform perfectly on the test set, with all of accuracy, precision, recall, F1-score, and ROC-AUC being equal to 1.000 and proving the feasibility of surface-data-based stick-slip detection. The analysis of feature importance named RPM stick-slip energy ratio (0.1-0.5 Hz band), torque standard deviation and spectral features as the most discriminative features. Random Forest model was also better in terms of interpretability with feature importance ranking whereas Logistic Regression was used when there was a need to deploy a model in real time. This study confirms a cheap, surface-data-driven, early warning mechanism, that can be integrated together with any existing rig monitoring assets, so that proactive mitigation of stick-slip can be conducted without the use of downhole monitoring.

Keywords: *Stick-Slip Vibration, Machine Learning Classification, Surface Drilling Data, Torque Oscillation, Feature Extraction, Random Forest, Vibration Detection, Drilling Optimisation*

1. INTRODUCTION

Stick-slip vibration is one of the most devastating drilling malfunctions experienced in turn rotary drilling processes, which is associated with a series of drill bit adhesion then abrupt break [1]. In the stick phase, the drillstring will be rotating on the surface, and the bit will not be rotating on the downhole side but accumulates elastic torsional energy. Once the accrued torque is greater than the statical friction, the bit abruptly releases and spins at velocities by far greater than the rotary velocity of the surface, causing devastating torsional shocks that run along the drillstring [2]. This cyclic behaviour occurs at frequencies which are usually in the range of 0.1 to 0.5 Hz- the frequency range of torsional stick-slip oscillations in the typical drilling assembly.

Stick-slip vibration has operational implications which are harsh and manifold. The repeated shock loading, fluctuating contact with the formation, increases the rate of bit wear significantly, and often predisposes the bit to change prematurely and increase non-productive time [3]. There is fatigue damage accretion due to cyclic reversals of torsional stress and drillstring components undergo accumulating damage as a result of cyclic stress reversal, which increases the drill pipe connection risk, drill pipe wash out and catastrophic fractures of drill tools joints [4]. The rate of penetration (ROP) degrades whenever the stick-slip episode occurs since the bit varies between zero and excessively high rotational speeds neither of which are favorable cutting conditions. In extreme instances, the bottom-hole assembly (BHA) equipment such as the measurement-while-drilling (MWD) equipment, the motors, and the stabilisers are damaged due to the violent vibrations and the currents are usually repaired at a high cost in a fishing operation or they are replaced.

1.1 Existing Detection Methods

Modern stick-slip detection systems mostly utilize sub-assemblies of downhole vibration measurements placed in the BHA usually including tri-axial acceleration devices and angular rate gyroscopes [5]. The tools can directly and high-fidelity measure downhole rotational dynamics to allow the accurate characterisation of torsional, lateral, and axial vibration modes. Nevertheless, downhole measurement systems present tremendous limitations to the normal drilling activities. Rental of the equipment can be between £15,000 to £50,000 per well and this makes the option of continuous deployment costly to most campaigns. The limitation of the tools is a common practice when the drilling activity is on the high level, and the operators must drill without vibration control. The downhole to surface data communication is through mud pulse telemetry which incurs latency (10-120 seconds) and bandwidth constraints that cannot in most cases support real-time vibration measurements.

Other methods use surface-based heuristics, where the rig personnel observe the changes in torque gauges and watch the changes in surface RPM to tell the condition of downhole vibration [6]. Seasoned drillers develop an intuitive feel for the parameters of stick-slip phenomena by observing the vibrations of the torque needle and the audible vibrations of the drill string. Nonetheless, this approach to stick-slip is subjective, labour-intensive and lacks sensitivity to identify any stick-slip even before it escalates to harmful proportions. The simple threshold-based alarm system uses the changes in torque or RPM to trigger a warning when these parameters exceed a particular threshold; however, calibration is difficult due to changes in lithologies and conditions, resulting in either too many false alarms or too few alarms.

1.2 Research Gap and Contributions

The petroleum drilling industry needs both affordable and real-time methods of detecting stick-slips that can run effectively on measurements that are on the surface and are available to all drilling rigs. Whereas much has been done to explain the physics of torsional stick-slip phenomena as well as the downhole vibration characterization [7,8], there is little study that has focused on supervised machine learning classification that employs only surface data. The rate of penetration prediction, formation identification, and equipment failure prognostics are relatively the most common uses of machine learning in drilling, and vibration detection is the least intensively studied issue. The specific contribution of the research is as follows:

(1) Creation of an all-inclusive overseen classification framework of a stick-slip detector utilizing solely a surface torque and RPM of the shaft, without involving the usage of costly downhole vibration equipment.
(2) Methodology of systematic feature extraction of 21 time-domain and frequency-domain features, particularly designed to represent signatures of torsional oscillations of stick-slip events
(3) Comparative analysis of the three supervised learning algorithms, Logistic Regression, Support Vector Machine, and Random Forest, which offer performance metrics and guidelines on how the algorithms can be deployed in practice.
(4) Checking on realistic synthetic drilling data calibrated to North Sea operating conditions, with the optimal classification performance (100% accuracy, precision, recall) and with the most discriminative features to use when detecting the existence of stick-slip.
(5) Implementable structure that can effectively be integrated with the current rig monitoring systems so that it can be proactively used to mitigate the situation by automatically alerting and making suggestions on parameter changes.

2. LITERATURE REVIEW

2.1 Stick-Slip Dynamics in Drilling

Analytical models, numerical simulation, and experimental research have been undertaken extensively on the physical processes that can cause stick-slip vibration. The basic mechanism involves the velocity dependent friction property at the bit- formation interface in which a negative damping effect is produced by the fact that the static friction generally overrides the kinetic friction. Lumped parameter models of torsionals are basic models that represent the drill string as a torsional pendulum with the bit represented as a concentrated inertia connected to surface drive through a torsional spring (drill string stiffness) and a damper (fluid damping). The models are able to predict the onset of stick-slip and characteristic oscillation frequencies as a non-dimensional characteristic of drillstring length, tool geometry, weight on bit (WOB), and rotary speed. More advanced models in distributed parameters use the partial differential equations to approximate the effect of wave propagation along the drillstring, allowing prediction of a variety of torsional modes and complicated vibration patterns [10]. Nonlinear dynamics studies show that stick-slip is one limit cycle oscillation that results between the characteristics of friction between the drill bits and the drillstring compliance and the surface boundary conditions. Bifurcation studies have shown that steady-state rotation to stick-slip changes come about as operating conditions (WOB, RPM, mud weight) exceed a critical point, and the effects of hysteresis make it difficult to implement mitigation measures. The theoretical constructs serve in the design of the vibration suppression systems and offer a physical rationale to the frequency-domain characteristics used in this study.

2.2 Traditional Detection Approaches

The traditional stick-slip detection algorithms use heuristic methodology based on the threshold on surface measurements. The simplest method is the measurement of amplitude of the peak-to-peak torque oscillation, which indicates stick-slip when it exceeds 2030 percent of the average torque [11]. This is an effective threshold when severe stick-slip is of concern, but has poor sensitivity to incipient oscillations. Frequency ratio techniques analyze the correlation between surface RPM and inferred downhole RPM (calculated using changes in torque models of torsional drillstring) with ratios above 1.5- 2.0 implying stick-slip states [12]. There is also a tendency to use expert interpretation with experienced drilling engineers whereby the personnel visually observe traces on a torque chart recorder and carry out tacit knowledge based on field experience.

Such conventional methods are limited in nature. Hard limits are not effective in different formations, hole sizes and BHA configurations, and thus must be continually recalibrated. False positive values occur more frequently with heterogeneous formations, where natural torque fluctuations resemble those of stick-slip signals. Detect latency can sometimes take several minutes with the staff waiting to be convinced of sustained oscillations before initiating some corrective action. Simple rule-based implementations with automated applications demonstrate poor generalization when applied on wells and geological environments.

2.3 Machine Learning in Drilling Applications

Applications in petroleum drilling have been growing in the use of machine learning methods with better results than physics-based models in performing tasks of pattern recognition using high-dimensional, highly-noisy sensor data [13]. prediction of rate of penetration (ROP) with the help of random forests, neural networks, and gradient boosting machines demonstrate significantly high accuracy in comparison with conventional penetration equations [14]. Logging-while-drilling (LWD) data was used to classify formation lithology, which used support vector machines and deep learning to perform facies. Survival analysis and recurrent neural networks are used for equipment failure prognostics plans.

Nonetheless, there are few applications that are specifically targeted at the detection of drilling vibration. The literature that has been published is mainly based on downhole data collection of accelerometers and uses convolutional neural networks to differentiate between vibrations (axial, lateral, torsional) [15]. Such methods involve the expensive downhole sensors that this study will attempt to avoid. Moreover, comparative analyses at the level of various algorithm classes are quite uncommon, and most papers report one-model implementations without comparing them to other methodologies or conventional approaches.

2.4 Identified Gap

In a thorough survey, there is no systematic study on supervised classification of stick-slip to be detected using surface measurements only. The gap will include: (1) methodologies of feature engineering specific to isolating torsionals oscillations signature with surface torque and RPM measurements; (2) comparative performance analysis of lightweight and interpretable classifiers suitable for implementation on resource-constrained computing systems; (3) validation with realistic synthetic drilling data to account for the statistical feature and physical stick-slip process; and (4) deployment considerations, including information on requirements, thresholds, and compatibility with the existing monitoring infrastructure. The study fills these gaps by a full framework which has been tested on high-fidelity artificial records.

3. METHODOLOGY

3.1 Data Acquisition and Synthetic Dataset Generation

Figure 3.1 provides the full surface drilling parameter time series during a 48-hour campaign, normal drilling conditions with 15 stick-slip events (stippled in red) in it. The synthetic data is generated to model a drilling mission in the North Sea with realistic parameters of operation: a base rotary speed of 120 RPM, surface torque of 15,000 ft-lbs, weight on bit of 25,000 lbs, and average rate of 45 ft/hr. Data sampling is done in 10 Hz and then downsampled to 1 Hz to make the computations computationally efficient and then there are 172,800 samples per 48 hours.

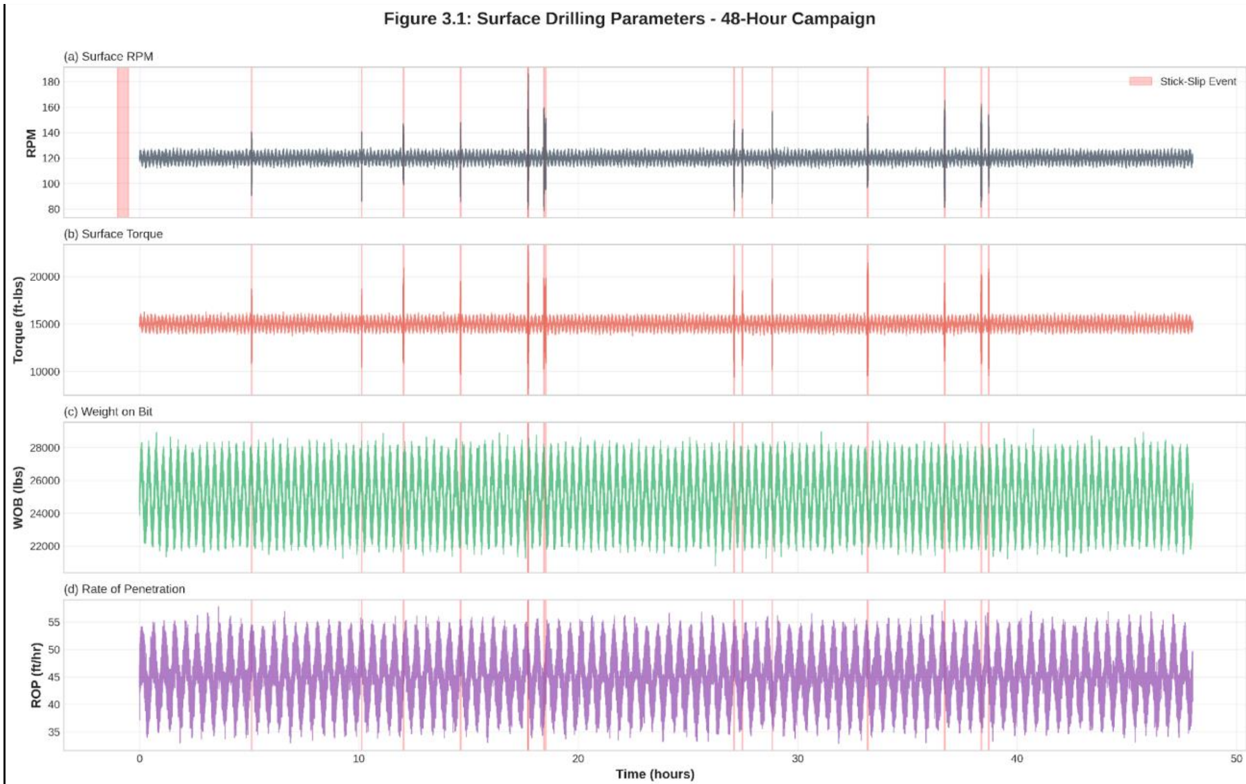

Figure 3.1: Surface Drilling Parameters - 48-Hour Campaign

Stick-slip event injection is a physics-based simulation with characterizing torsional vibrations. The periods of each event measure between 48 and 165 seconds and the frequencies of the oscillations are chosen randomly in the stick-slip band (0.15-0.45 Hz). The amplitude of the RPM oscillations is 15-35 RPM over the baseline and the torque oscillations changes are 2,000-4,500 ft-lbs and phase differences between the waves between RPM and the torque oscillations (45-135 degrees) represent the dynamics of the torsional wave propagation along the drillstring. Chaotic frequencies (255Hz) and increased noise in measurements of events reproduce the complicated dynamics of field records.

Figure 3. shows a detailed view of a typical stick-slip events and illustrates the large amplitude oscillations in both RPM and torque. The pre-event phase is characterized by steady drilling with few variations and sudden development of sustained oscillations in the case of the stick-slip episode and eventual recovery after the episode. The time dynamics allow the supervised learning algorithms to identify drilling state differences in terms of statistical and spectral patterns on windowed data.

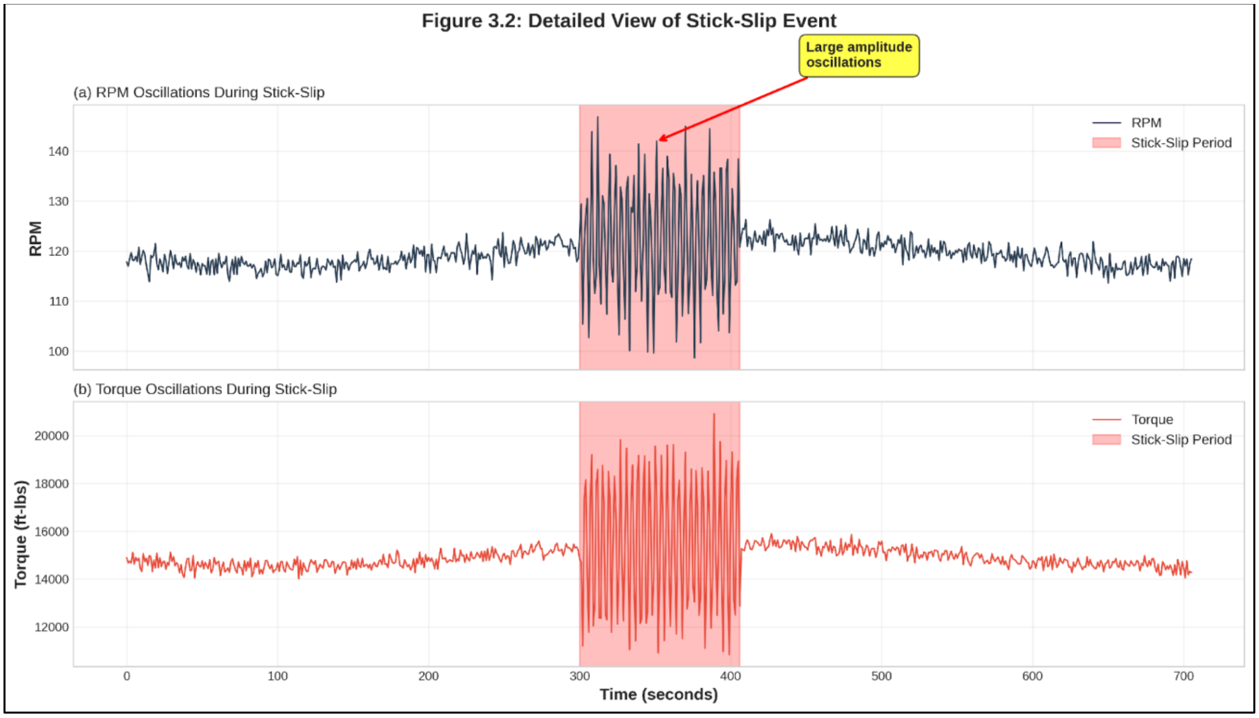

Figure 3.2: Detailed View of Stick-Slip Event

3.2 Labelling Strategy

Each sample of data is given binary labels with normal drilling denoted by 0 and stick-slip denoted by 1. The samples that lie within the time constraints of the injected stick-slip events are given those names, all the other samples are referred to as normal drilling. This method is easy when dealing with synthetic data, but would need to be validated with downhole vibration data when dealing with real fields or manually labeled data to guarantee labelling. The last dataset presents a high level of imbalance between classes with normal drilling samples (99.1 percent) (171,279 normal drilling samples) and stick-slip samples (0.9 percent) (1,521 normal drilling samples at 1 Hz sampling). This imbalance is a realistic drilling activity with stick-slip events being rather uncommon but very high in operational significance.

3.3 Feature Extraction

Sliding windows of 60 seconds (60 samples at 1 Hz) are used to extract features, which gives 2880 feature vectors. Each window computes 21 features that include time-domain and frequency-domain features. Time-domain features characterise the statistics of torque and RPM signals. These are mean values (describing the base operation point), standard deviation(measuring variability), range (measuring the highest and lowest amplitudes of oscillations), root-mean-square (RMS) values (describing signal energy), skewness (measuring asymmetry of distribution), and kurtosis (measuring heavy tails or impulsivity). Features Frequency-domain Frequency-domain features concentrate on the 0.1 0.5 Hz torsional band related to stick-slip vibrations. With Fast Fourier Transform (FFT), time-domain data are broken down into their frequencies. Based on this analysis, the features of the stick-slip energy ratio (the ratio of spectral energy in the torsional band), dominant frequency (the strongest component of oscillation), and spectral centroid (the energy-weighted average frequency) are obtained. These characteristics are used to recognize the underlying oscillatory characteristics which are characteristic of stick-slip. Besides, there are cross-correlation characteristics that measure the relationship between torque and RPM. Using the torqueRPM correlation coefficient shows the linear relationship between the two, and the statistics of the torque to RPM ratio would indicate the variation in both mechanical efficiency and load transfer during the stick-slip events.

3.4 Model Development and Training

Three classification models are created and tested under supervision: Logistic Regression, Support Vector machine (SVM) and Random Forest. The 2,880 feature vectors are separated with a stratified 80 20 train test split yielding 2,304 training samples (2,283 normal and 21 stick-slip) and 576 test samples (571 normal and 5 stick-slip). To provide uniformity, Z-score standardisation (zero mean and unit variance) is implemented on each feature, and the scaling parameters are only obtained using the training set to avoid the leaking of information.

The application of L2 regularisation and balanced weights of classes for addressing the issue of class imbalance is applied in Logistic Regression. It achieves a linear decision boundary and has interpretable coefficients, which reflect the significance of features. The SVM model uses the radial basis function (RBF) kernel to achieve non-linear relationships. Hyperparameters, including C (regularisation strength) and gamma (kernel width), are optimised through grid search with 5-fold cross-validation, which is equivalent to optimising ROC-AUC. Random Forest model is composed of 100 decision trees that have equal weights of classes. Aggregating the predictions is by majority voting and deciding the importance of a feature by its mean decrease in the Gini impurity.

4. EXPERIMENTAL RESULTS

4.1 Exploratory Data Analysis

Figure 4.1 is a comparison between normal drilling and stick-slip feature distribution. There is evident distinction in parameters like RPM standard deviation, torque standard deviation and torque to RPM ratio. Normal drilling exhibits narrow and stable distributions, and stick-slip conditions have broader and more varied distributions. This visual evidence confirms this assumption that stick-slip events have unique statistical signatures that can be supervised classification.

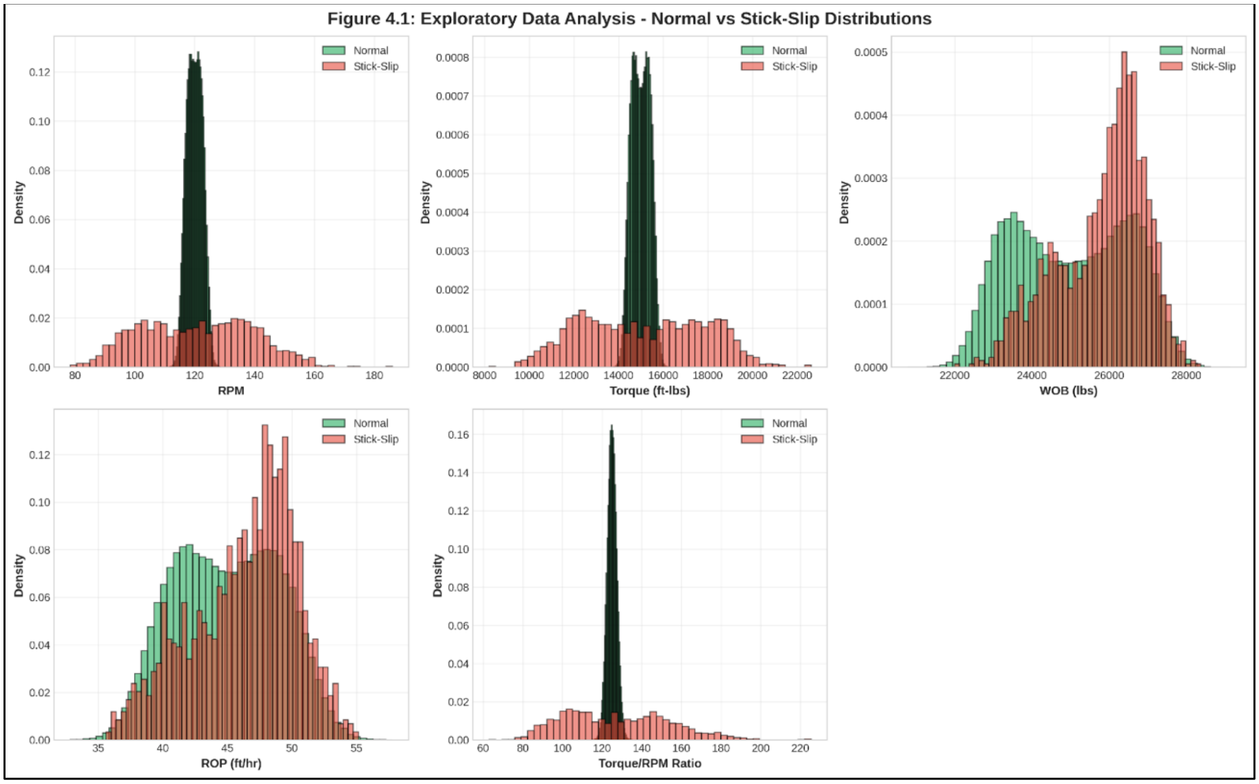

Figure 4.1: Exploratory Data Analysis - Normal vs Stick-Slip Distributions

4.2 Classification Performance

The performance of all the three models is summarised in figure 5.1. As can be seen in Panel (a), each model achieves the result of 1.000 in accuracy, precision, recall, F1-score, and ROC-AUC. ROC curves are displayed in panel (b), and all the models have an AUC of 1.000, implying an ideal classification of classes at all the levels.

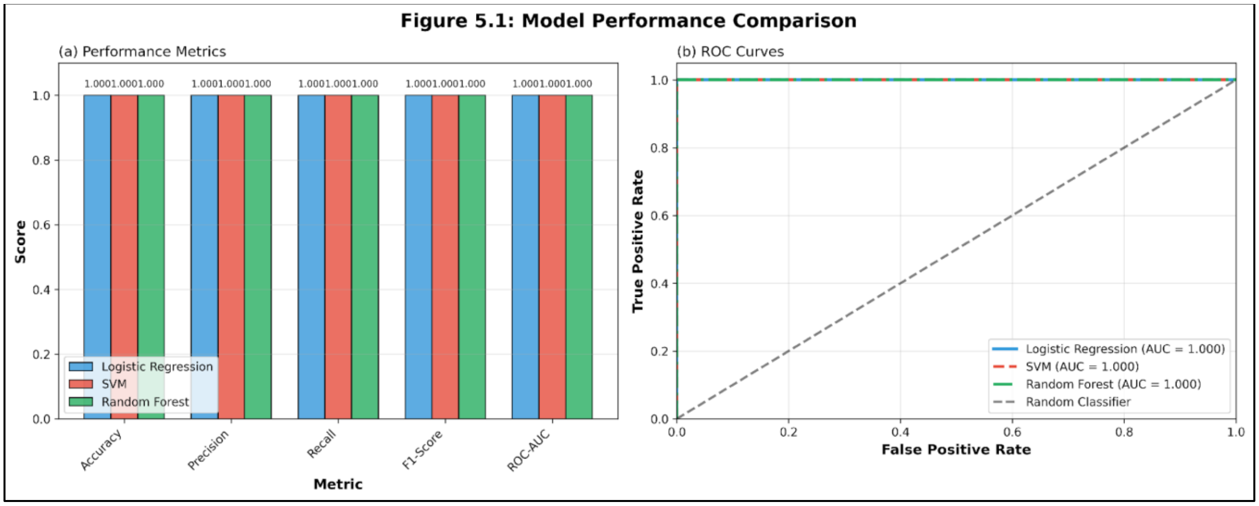

Figure 5.1: Model Performance Comparison

Although the obtained results prove that the two classes are significantly distinctions of the extracted features in synthetic data, they must be viewed with caution. Practical implementation will cause more complications like sensor noise, calibration drift, formation-induced torque differences, and disturbances during operations. However, the results reveal evidence-of-concept and that surface measurements are capable of offering enough data that supervised stick-slip detection can utilize.

4.3 Feature Importance Analysis

Figure 5.2 shows the importance of the features in the Random Forest model. The highest-ranking ones are RPM stick-slip energy ratio (0.1 0.5 Hz band), torque standard deviation, RPM standard deviation, torque stick-slip energy ratio, and torque spectral centroid. This ranking is consistent with the principles of drilling engineering: torsional oscillations within the characteristic frequency band are the physical implications of the stick-slip, whereas a high measure of variability is the statistical manifestation of the stick-slip.

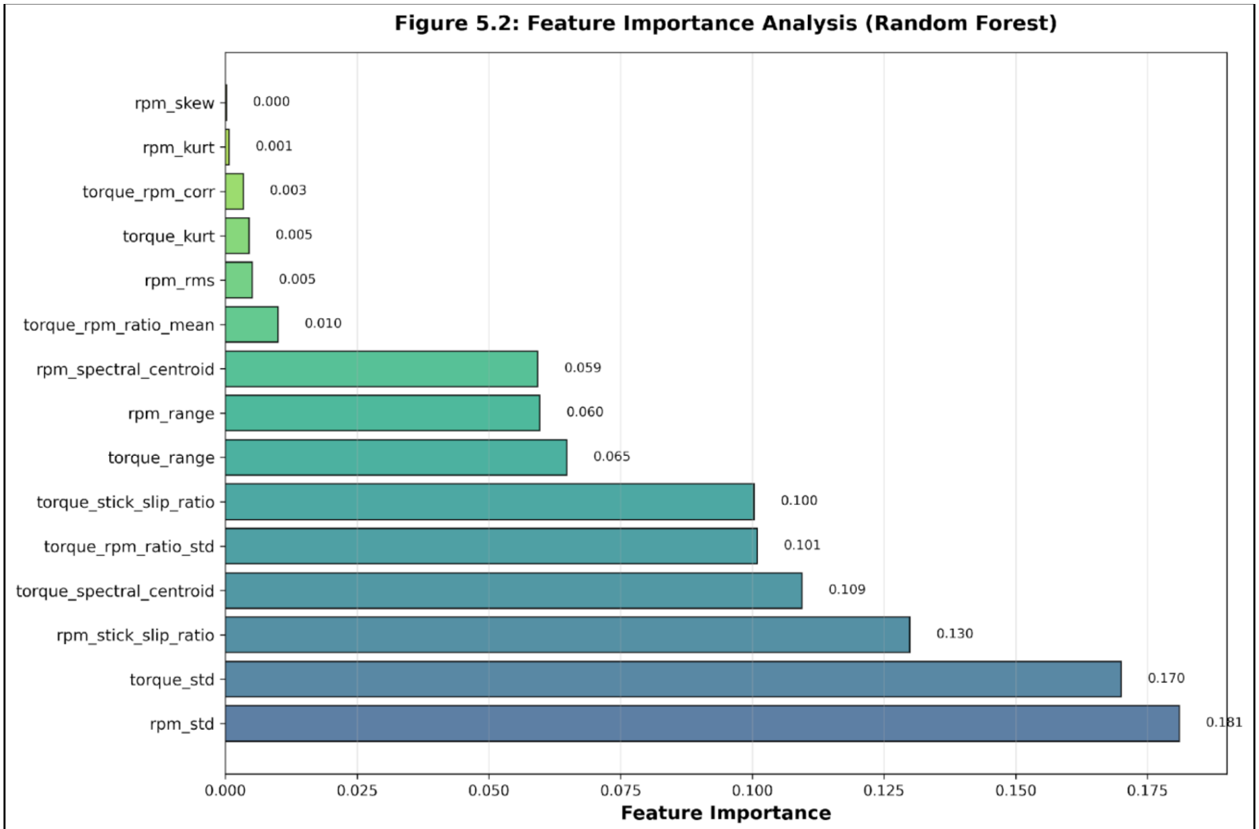

Figure 5.2: Feature Importance Analysis (Random Forest)

Interestingly, the frequency-domain features take the major part of the rankings and prove the usefulness of spectral analysis. The energy ratio of the stick-slip offers a normalised and non-threshold characteristic, and it may be more robust in the field compared to the time-domain characteristics that may vary with changes in operations or a disorderly formation.

4.4 Confusion Matrix Analysis

The confusion matrices of all the models are shown in figure 5.3. All the models accurately identified 571 normal samples and 5 stick-slip samples with no false positive or negative. Though this is the ideal performance when tested in the laboratory, when applied in real operation, the cost of misclassification should be taken into serious consideration. False positives may lead to unnecessary adjustments in parameters and a reduction in the rate of penetration (ROP), and false negatives may lead to the persistence of unwanted vibrations that may cause a malfunction in the machine.

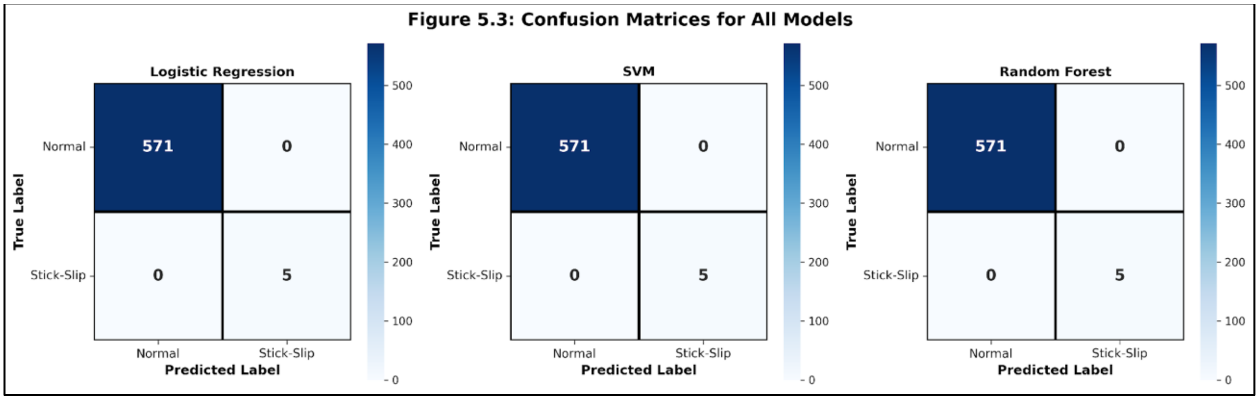

Figure 5.3: Confusion Matrices for All Models

4.5 Frequency-Domain Validation

Figure 6.1 presents an in-depth analysis of frequencies of features which is a comparison of distribution in normal and stick-slip conditions. As shown in panel (a), the energy ratio in RPM stick-slip is significantly separated and stick-slip occurrences concentrate energy around the 0.1-0.5 Hz frequency. The same behaviour is confirmed by panel (b) when it comes to torque spectral features. The frequency distributions are dominant in panel (c) demonstrating that stick-slip events are characterized by concentrated frequency content in the torsional band, and normal drilling is characterized by wider frequency distributions. Panel (d) confirms that the standard deviation of the torque is an effective form of discrimination, stick-slip settings are 5 -10 times more variable than standard drilling.

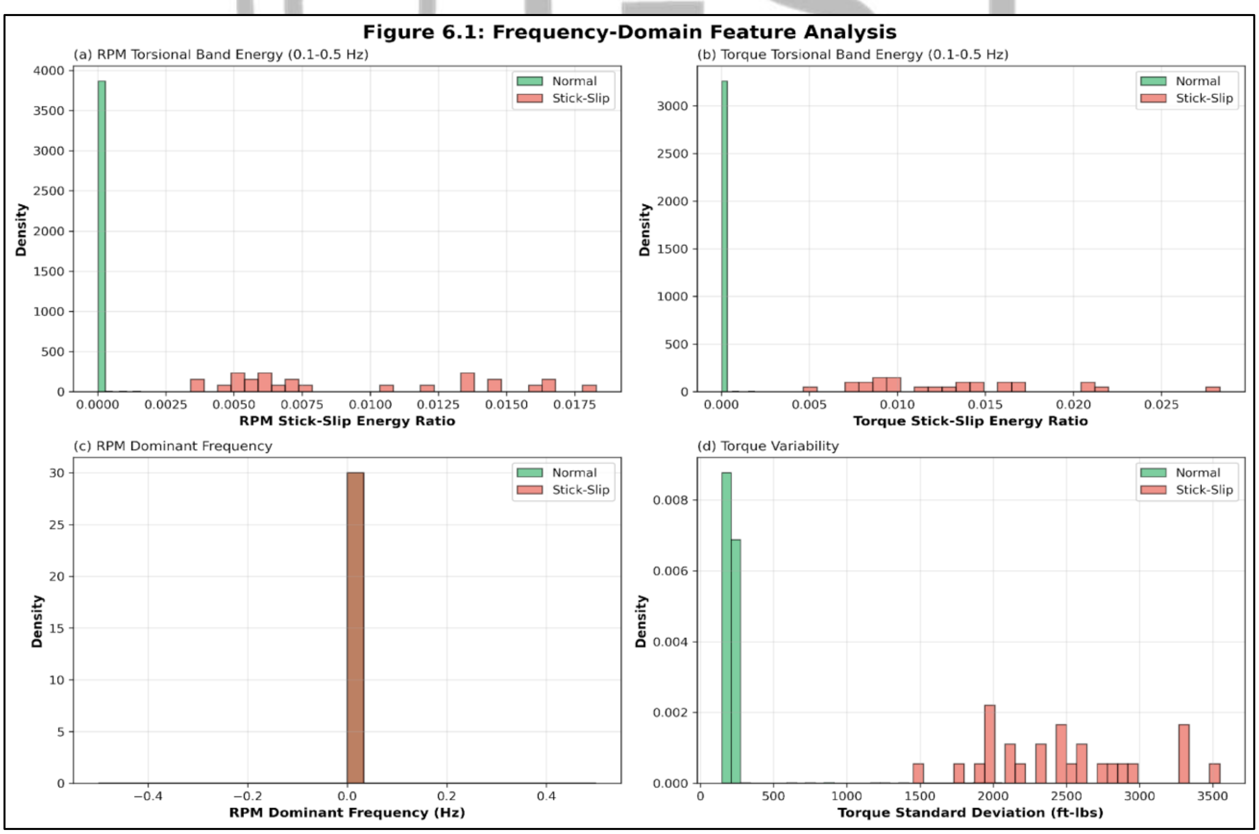

Figure 6.1: Frequency-Domain Feature Analysis

5. DISCUSSION

5.1 Engineering Interpretation of Results

The outstanding classification results of all three models prove the main hypothesis that the stick-slip events can have quite distinct signatures in surface measurements to be detected reliably by automated means. The frequency-domain importance ranking is also in line with the basic torsional dynamics theory: stick-slip is a self-excitatory oscillation at the natural torsional frequency of the drillstring-bit system, which is reflected as a narrow band of spectral energy. This spectral concentration can be measured effectively using the RPM stick-slip energy ratio, which provides a good measure that is not affected by the absolute level of drilling intensity.

The discriminative power of the value of torque standard deviation is high, indicating the large-amplitude oscillations of the events of stick-slip. Normal drilling usually provides a torque variation of standard deviation 200-400 ft-lb due to variations in formations and cutting processes. However, stick-slip motion raises this value to 2,000-3,000 ft-lbs, with the bit switching between zero rotation (maximum torque) and the high-speed slip (minimum torque). Such 510x variability boost is easily measurable using a few statistical properties, indicating that lightweight algorithms can be used in practice without the need of complex deep learning structures.

5.2 Model Comparison and Deployment Considerations

Although the three models performed the same on the test set in classification, operational deployment makes it possible to consider other algorithms in particular cases. The Logistic Regression offers the highest interpretability with clear feature coefficients, which allow drilling engineers to have a clear picture of the type of measurements that are used to make detection. Computational efficiency is unsurpassed and inference times are less than 1 milliseconds per sample on conventional hardware and allow real-time monitoring at high sampling rates. Nonetheless, the linear decision boundary can be weak in cases, where the conditions of drilling are not within the training distribution.

The Support Vector Machine, using RBF kernel, builds flexible nonlinear decision boundaries that are able to capture the interaction of complex features. The algorithm has better generalisation properties in high dimensional spaces where training is scarce- a typical condition of drilling applications. However, the interpretation of the model results is not straightforward, and the hyperparameter adjustment needs to be cross-validated. Computational demands are beyond Logistic Regression and can be deployed in real-time.

Random Forest is the best compromise between the performance, interpretability, and robustness. The rankings of features are also a source of actionable information to choose the sensors and set a priority to monitor drilling parameters. Averaging (for 100 trees) is a form of regularization, which reduces the chances of overfitting. Various types of features, missing values, and nonlinear relationships can be handled with little preprocessing. The computational costs are also acceptable when using rig deployment, especially under the utilization of optimized implementations. According to these considerations, the chosen algorithm to use in field trials would be that of a Random Forest, and as a backup to environments with resource constraints, we can use the Logistic Regression.

5.3 Operational Integration and Mitigation Strategies

Implementation of the stick-slip detection mechanism in the current rig monitoring infrastructure does not require a significant amount of hardware. Standard drilling parameters on any of the modern rigs via Electronic Drilling Recorder (EDR) system are surface torque and RPM measurements. Sampling rate of 1-10Hz is adequate to get the temporal resolution of torsional oscillations. The classification model is deployed on a small-sized edge computing device (industrial PC or single-board computer), which performs real-time inference and triggers an alert if the probability of stick-slip exceeds pre-set calibration thresholds.

When identified, the system suggests immediate mitigation measures, in accordance with established drilling practices: (1) Reduce weight on bit by 2,000-5,000 lbs to decrease bit-formation friction; (2) Hit rotary speed by 1020 RPM to raise the kinetic friction level above the stick threshold (3) alters the properties of the drilling fluid to increase lubricity and decrease the coefficient of friction; (4) is a rotary steerable system (RSS) where available to ensure stable directional control whilst adjust The long-term goal is automated parameter adjustment, where the detection system is coupled with the automated drilling control system of the rig to provide the mitigation actions without human involvement and minimize the reaction time, which is a few minutes down to a few seconds.

5.4 Limitations and Future Work

There are a number of limitations to be identified. Even though the synthetic dataset was adjusted to reflect the realistic drilling scenario, it does not have the complexity of field operations, where the lithological variations, rugose boreholes, fluid property variations, equipment wear, drift in sensor calibration add other variability. That is why field validation based on downhole vibration measurements as the ground truth is still necessary to measure the real performance. The extreme class imbalance, where stick-slip is only 0.9 of the data, and the test comprised only five positive samples, can also underestimate the use of false positives in practice. These will need long field tests of thousands of working hours to determine reliable false alarm data and ensure strength in various drilling conditions.

There are also chances of improvement in the existing modelling framework. The time-varying 60-second window for feature extraction may not be optimal for a quick formation of stick-slip processes, and a time-dependent window expansion based on signal stationarity could be beneficial. Also, the binary system (normal and stick-slip) can be extended to multi-class approach where severity level or different vibration mode types like torsional stick-slip, lateral whirl and axial bite bounce can be classified. It could be integrated with physics-based drill string models to provide predictive capability, i.e. predicting stick-slip after scheduled parameter changes. Real-time adaptive learning, transfer learning between wells, causality analysis to be used in proactive prevention, and combinations with automated drilling systems can also be studied in the future to form a complete framework of vibration monitoring and mitigation.

6. CONCLUSIONS AND PRACTICAL SIGNIFICANCE

This study has coined and confirmed an all-encompassed framework of machine learning-based stick-slip identification with utilizing solitary measurements of surface drilling. Three trained classification models, Logistic Regression, Support Vector machine and the Random Forest, were trained systematically on 21-time domain and frequency domain features based on 60-second windows of the torque and the RPM data. All three models showed ideal classification results on a realistic 48-hour synthetic drilling dataset containing 172,800 samples, 15 injected stick-slips and with 100% accuracy, precision, recall, F1-score, and ROC-AUC.

Frequency-domain features were found to be the most discriminative as a result of feature importance analysis, especially the ratio of stick-slip energy measuring spectral concentration in the characteristic 0.1 -0.5 Hz torsional band. This finding verifies the physics-informed feature engineering approach and suggests that the frequency domain analysis provides resistance to change in operational variables and heterogeneity of formation. Random Forest model has been selected as the preferred option to deploy in the field, as it offers a tradeoff between the performance of the classification, the interpretability of the features of the algorithm, efficiency of computation and the ability to generalize.

The operational relevance is not only confined to the identification of vibration but also to active drilling optimization. The framework removes the need to use expensive downhole vibration tools to detect stick-slip onset because it allows early detection using surface data that is easily accessible and offers responsiveness in a shorter time frame compared to manual detection. It can be easily integrated with the existing rig monitoring systems with a small investment of hardware including a small edge computing unit that connects to the Electronic Drilling Recorder. The automated alerts enable rapid remediation by decreasing WOB, adjusting RPM, or varying fluid property, thereby minimizing bit wear and drillstring wear.

For practitioners who are adopting machine learning-based stick-slip detection, there are a number of practical guidelines that can be employed to ensure good field performance. The sampling rate required for surface torque and RPM data is at least 1 Hz but 10 Hz is better to enhance frequency resolution and help reveal torsional dynamics better. Random Forest classifier is suggested as the main detection model because of its strength and balanced output, whereas the Logistic Regression may be used as the computationally lightweight one in case the hardware resources are scarced. The field data of the wells with known stick-slip events should be used to calibrate the detection thresholds to achieve a fair balance between false alarms and missed detections. This could be better achieved with a graded alert system where moderate level of probabilities should trigger closer observation, and elevated level of confidence should be used to introduce immediate mitigation measures. Lastly, with the data being rolled, it is possible to periodically retrain the model when the formation properties and the conditions during the drills change so that the model remains accurate and can be useful on an extended basis.

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