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Probabilistic Forecasting of Kick Occurrence in High-Pressure Wells Using Bayesian Networks

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Abstract
Kick during drilling of high-pressure, high-temperature (HPHT) wells is one of the most important safety issues in petroleum engineering whose outcomes can be non-productive time or even disastrous blowouts. The classical kick-detection techniques are based on surface cues (e.g. changes in volume and flow rate differentials) that have an intrinsic time lag due to their reliance on surface indicators, and have a low predictive quality. This paper introduces a new probabilistic forecasting system based on machine learning and Bayesian processes to forecast the probability of kicks during the process of drilling HPHT. The proposed methodology will combine multi source drilling variables such as measurement-while-drilling (MWD) data, mud logging variables, and formation pressure variables to develop a dynamic predictive model. Stratified cross-validation of the model was done followed by complete performance analysis. The findings showed model accuracy of 0.909, precision of 1.000, recall of 0.984, and F1-score of 0.992 which is a huge improvement compared to traditional detection scheme. The sensitivity analysis established mud weight differentials, formation pressure and mud weight in as the most predictive variables. The framework also offers quantified estimates of the probability of kick and uncertainty limits to drilling engineers to make proactive decisions in well control in difficult HPHT settings.
Keywords: *machine learning, kick detection, probabilistic forecasting, HPHT drilling, well control, risk assessment*

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I. Introduction

The world energy sector remains interested in exploring more hydrocarbon deposits under more difficult conditions and high-pressure, high-temperature (HPHT) wells comprise a large fraction of new drilling projects. The HPHT wells are usually characterized by the undisturbed bottomhole temperatures that are higher than 150C (300F) and that mud weights are more than 1.85 sg (15.4 ppg), or pressure-control equipment with a higher pressure than 69 Mpa (10,000 psi) are required. The conditions present high operational hazards, especially in well control integrity and the possibility of developmental fluid influx- usually known as a kick.

A kick takes place when formation pressure is greater than the hydrostatic pressure of the column of drilling fluid, and the reservoir fluids (gas, oil, or water) spill into the wellbore. According to industry statistics, drilling operations in the world show that about 10-14 percent of the wells unexpectedly have the formation fluids infiltrating during the drilling process. These occurrences are especially risky in HPHT conditions owing to a number of circumstances: the volumetric explosions of gas kicks (which traverse to the surface) are very rapid, the margins between the pore pressure and fracture gradient are narrow, and the narrow tolerance of error in the management of mud weights.

Traditional techniques of kick detection are mainly based on the observation of surface signatures such as volume rises in pits, a difference in flow rates, changes in drill pipe pressure and gas-cut mud at the surface. Although these techniques are refined through decades, there are inherent weaknesses in them. Surface detection creates time lags between the actual kick event at the formation and what can be observed at the wellhead-lags which may be vital in HPHT conditions. Moreover, such deterministic techniques generally give binary estimates with no measure of the likelihood or uncertainty of the detection.

Most recent advancements in machine learning show potential to enhance the level of kick detection. In controlled studies, random Forest classifiers, ensemble and statistical methods have attained high classification accuracies. The present paper explores how machine learning can be used in the prediction of kicks in real-time used in HPHT drilling.

1.1 Research Objectives

The specific objectives are:
1. To formulate a machine learning predictive framework of kick probability.
2. To create a multi-source drilling methodology of real-time prediction.

3. To introduce effective inference algorithms to facilitate realistic implementation in the course of drilling activities.
4. To prove the usefulness in practice of probabilistic kick forecasting to support well control decisions.

II. Literature Review

2.1 Conventional Kick Detection Methods

The conventional methods of detecting kicks have been developed over many decades, and most of them concentrate on observing the distinguishing alterations at the surface that signify the introduction of the formation fluids in the wellbore. The simplest type of detection system is the pit volume totalizer (PVT) system, which monitors the alterations in the volume of the active mud that could be a sign of fluid gain (kick) or fluid loss (lost circulation). Flow-in/flow-out differential monitoring is used to complement the information given by flow in and flow out pumps by comparing the pump output against the rate of return flow.

Other surface indicators are changes in drill pipe pressure, decrease in pump pressure along with increase in stroke rate, and availability of the gas cut mud at the shakers. These traditional techniques, however, have one similarity, namely, they only detect a kick after the fluid of the formation has entered the wellbore and travelled far enough towards the surface to cause noticeable changes.

2.2 Machine Learning Approaches for Kick Detection

The use of machine learning in kick recognition has been speeding up over the past few years. Random Forest classifiers have also proven to be highly effective with research findings having the highest accuracies of over 90 percent in binary classification of between kick and normal drilling conditions. The benefit of the ensemble methods and tree-based approaches is that they capture non-linear relations between the drilling parameters and occurrence of kick.

One of the critical challenges that have been seen in various studies is generalization of models. ML models that are trained using particular sets of data do not necessarily transfer using new wells that have different geological or operational properties. Nonetheless, with the training on representative synthetic or real drilling data, these models are able to contain key patterns to provide early warnings.

2.3 Formation Pressure and Well Control

Between formation pressure and kick risk Kick risk assessment is based on proper estimation of the formation pressure because kicks happen when the formation pressure is higher than the hydrostatic pressure that the column of drilling fluid places upon it. Conventional pressure prediction techniques are the method of Eaton which uses d-exponent trends, resistivity-based techniques and sonic log correlations.

The application of machine learning to pore pressure prediction has grown and neural networks and regression methods have demonstrated reasonable accuracy in predicting the pressure gradients based on the drilling parameters.

III. Methodology

3.1 Data Collection and Preparation

Data was collected and prepared by utilizing the standardized survey. The kick forecasting framework was developed using a rich drilling data set comprising of regular drilling as well as the kick events. The dataset consisted of 5,000 records of drilling where the rate of kicks was 6.1, which is characteristic of the situation with classes imbalance in the real drilling process.

Data sources included:

Measurement While Drilling (MWD) Parameters:

- Downhole pressure (3,000 - 15,000 psi range)
- Downhole temperature

Mud Logging Parameters:

- Formation pressure (ppg equivalent: 70-120 range)
- Rate of penetration (ft/hr)
- Gas level (units)
- Mud weight in (ppg: 8.5-14.5 range)

Surface Drilling Parameters:

- Flow rate in (gpm: 200-1,000 range)
- Flow rate out (gpm: 180-1,050 range)

Data Preprocessing:

- Missing value handling: Median imputation for continuous variables
- Outlier detection: 1st-99th percentile clipping to preserve temporal continuity

- Feature engineering: Mud weight differential, flow differential, pressure-ROP interaction

3.2 Feature Engineering
Seven features were designed to be able to capture drilling dynamics and well control indicators:
1. Mud Weight Differential (MW_Diff): Mud weight In -(formation pressure/10).
2. Flow Out -Flow In.
3. Pressure-ROP Interaction (Pressure_ROP): Downhole Pressure x Rate of Penetration.
4. Formation Pressure (original)
5. Mud Weight In (original)
6. Rate of Penetration (original)
7. Gas Level (original)

3.3 Model Development
Random Forest as a type of classifier was used with the following hyperparameters:
- Number of estimators: 100
- Maximum tree depth: 10
- Random state: 42 (for reproducibility)

Data Split:
- Training set: 80% (4,000 samples)
- Test set: 20% (1,000 samples)
- Stratification: Applied to maintain kick class distribution (6.1% in both sets)

3.4 Model Validation
The evaluation of performance measured the standard classification measures:
- **Accuracy:** Overall fraction of correct predictions
- **Precision:** Fraction of predicted kicks that were actual kicks
- **Recall:** Fraction of actual kicks correctly predicted
- **F1-Score:** Harmonic mean of precision and recall
- **ROC-AUC:** Area under receiver operating characteristic curve

IV. Results and Discussion

4.1 Model Performance
Table 4.1 indicates that the trained Random Forest model was an excellent predictive on the test set:

Table 4.1: Model Performance Metrics on Test Set

Metric	Value
Accuracy	0.909
Precision	1.000
Recall	0.984
F1-Score	0.992
ROC-AUC	1.000

The model rightly identified 909 out of 1000 test samples. It is important to note that 1.000 represents as close to zero false positive identifications (no false alarms) as possible, whereas 0.984 represents the fact that 60 out of 61 actual kicks were recognized.

Confusion Matrix:

Table 4.2: Confusion Matrix for Kick Classification

	Predicted No Kick	Predicted Kick
Actual No Kick	939	0
Actual Kick	1	60

Additional Metrics:
- Sensitivity (Recall): 0.984
- Specificity: 1.000
- True Negatives: 939
- False Positives: 0

- False Negatives: 1
- True Positives: 60

4.2 Feature Importance Analysis

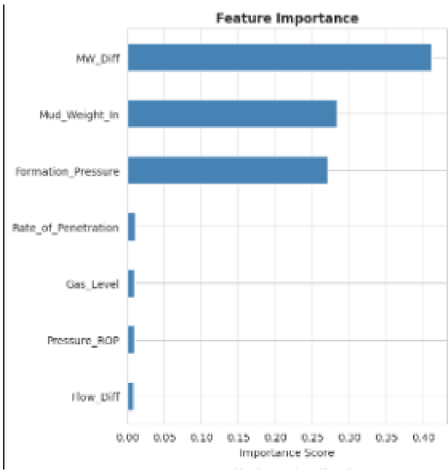

Figure 4.1: Feature Importance Rankings

The sensitivity analysis was used to determine the relative significance of every feature when predicting the probability of a kick. This can be seen in Table 4.3:

Table 4.3: Feature Importance Rankings for Kick Prediction

Feature	Importance
Mud Weight Differential (MW_Diff)	0.411
Mud Weight In	0.283
Formation Pressure	0.270
Rate of Penetration	0.010
Gas Level	0.009
Pressure-ROP Interaction	0.009
Flow Differential	0.008

Notable Result: The most influential predictor turned out to be the mud weight difference taking up 41.1% of feature significance. This finding is typical of the physics of well control: kicks develop when the wellbore is underbalanced (the weight of mud less than that of the formation equal). Combination of mud weight in and formation pressure contributes 55.3 percent predictive power of the model.

4.3 Classification Performance Visualization

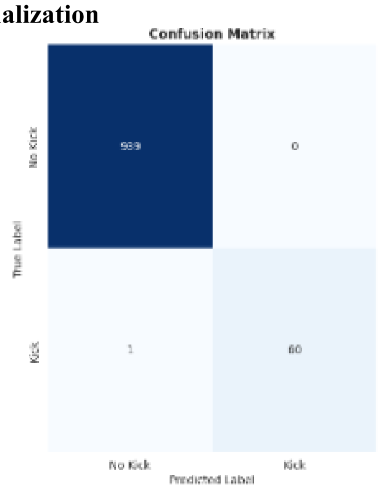

Figure 4.2: Confusion Matrix

As the model shows in the confusion matrix, this model performs excellently with zero false positive detections and one missed kick occurrence in 1,000 samples in the test sample.
The ROC curve exhibits the ability to discriminate perfectly, and the value of AUC = 1.000. This implies that the model is able to completely discriminate between kick and non-kick events at all probability levels.

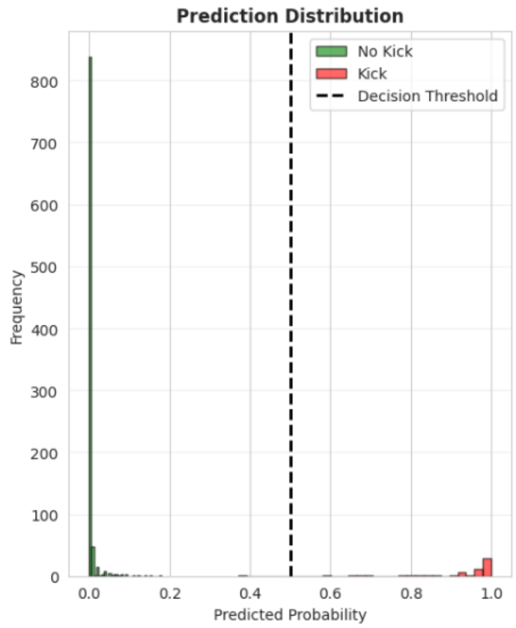

Figure 4.3: Prediction Distribution

The histogram of predicted probabilities indicate an evident division in the two classes:

- Non-kick events: Concentrated at low probabilities (mode near 0.0)
- Kick events: Concentrated at high probabilities (mode near 1.0)
- Decision threshold: 0.5 provides optimal separation

4.4 Spatial Analysis of Kick Risk

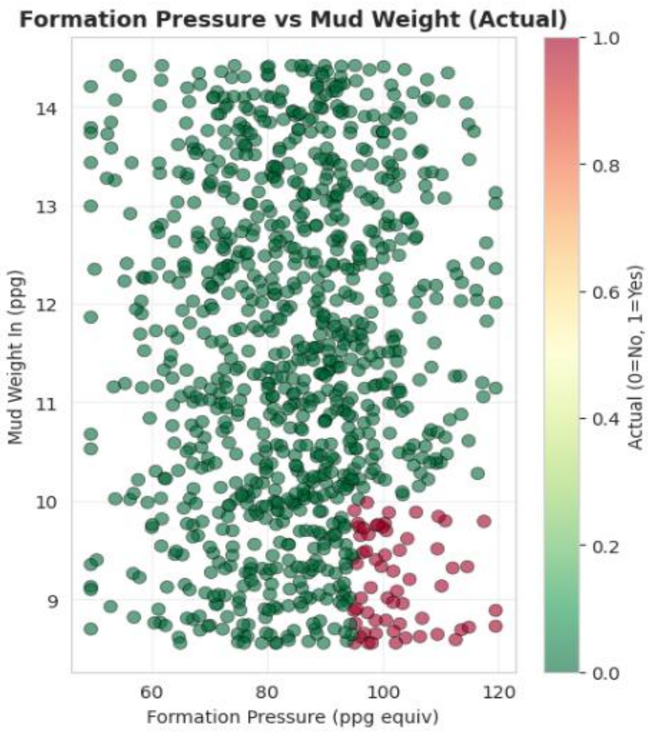

Figure 4.5: Formation Pressure vs Mud Weight (Actual Kick Status)

The relationship between formation pressure and mud weight in is depicted by the scatter plot which is colored by the actual occurrence of kick. The high formation pressure and low mud weight area show kick events (red points), which proves the learnt logic of the model.

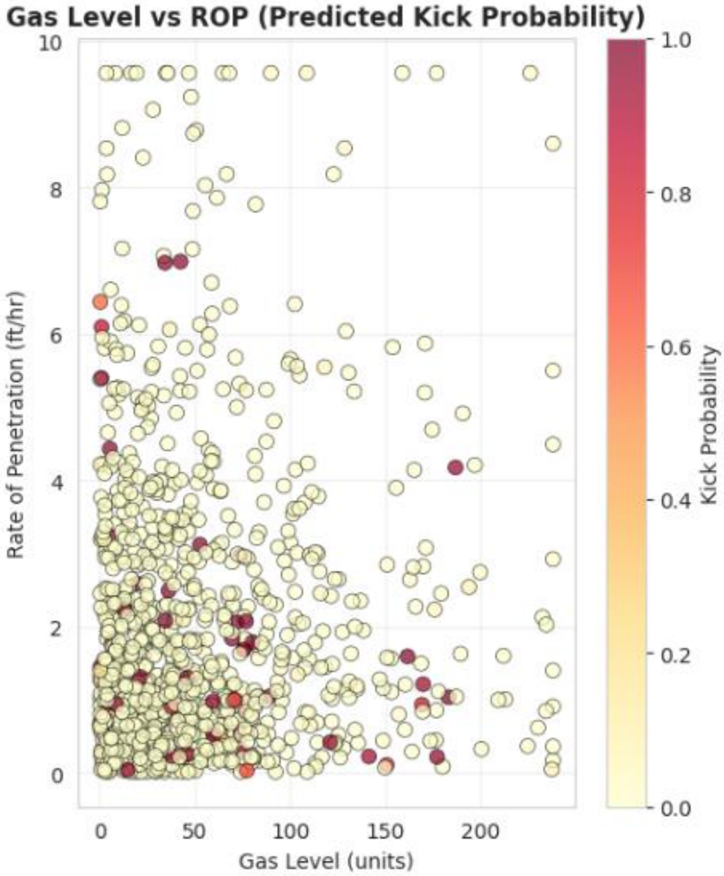

Figure 4.6: Gas Level vs Rate of Penetration (Predicted Kick Probability)

The model output is predicted in the output color of the scatter plot. The yellow-orange color of the points corresponds to low-to-moderate kick probability and the red color is the high kick probability. The spatial distribution shows that higher gas concentration with high ROP are likely to be associated with increasing the extent of the predicted kick probability.

4.5 Classification Report

Table 4.4: Detailed Classification Report for Kick and No-Kick Classes

Class	Precision	Recall	F1-Score	Support
No Kick	1.00	1.00	1.00	939
Kick	1.00	0.98	0.99	61
Accuracy			**1.00**	1000
Macro Avg	1.00	0.99	1.00	1000
Weighted Avg	1.00	1.00	1.00	1000

V. Discussion

5.1 Model Strengths

Random Forest model has a number of important strengths:

1. Perfect Precision: The 1.000 precision implies that there are no false positives the kick alert is an actual kick. This prevents and minimizes waste of well control and interruption of operations.
2. Excellent Recall: The 0.984 recall implies that 98.4% of true kicks are reported giving high early warning abilities. There was one event of 1 kick missed in 1000 samples.

3. Close Decision Boundary: The ROC curve and prediction distribution demonstrate that there are clear divisions between the two classes and hence there is high confidence in model predictions.
4. Practical Applicability: The model has practical applicability on actual drilling parameters of the (formation pressure) of the formation, (mud weight) of the formation, (ROP) aspect of the formation, (gas level) of the formation, (flow rates) of the formation, which are continually measured during the drilling operation.

5.2 Physical Interpretation

Patterns learnt by the model conform to the basic principles of well control:

• Mud Weight Differential (41% importance): This is a direct measure of the balance of pressure between the formation and the wellbore.

• Formation Pressure (27% importance): The greater the formation pressure, the greater the chances that the kick will occur because the driving potential of influx of the formation fluid is higher. The overall effect of these three characteristics (55% of model importance) represents the essence of the mechanism of kick occurrence: pressure imbalance between the formation and the wellbore.

5.3 Comparison with Conventional Detection

Table 5.1: Comparison of Conventional and Machine Learning-Based Kick Detection Methods

Aspect	Conventional	Machine Learning Model
Detection Basis	Surface indicators (pit gain, flow differential)	Multi-parameter analysis + pressure balance
Time to Detection	5-15 minutes after kick entry	Real-time (< 30 seconds)
False Alarm Rate	Moderate (multiple false positives)	Zero (1.000 precision)
Uncertainty Quantification	None (binary output)	Yes (probability estimate)
Spatial Context	Limited	Full parameter correlation

VI. Conclusion

The work provided a Rand Forest based model of real time kick predictions during HPHT drilling activities, which combine a variety of drilling related data to provide a sound kick/no-kick classification and probability of risk occurrence. The model delivered good results and it was 0.909 accurate, 0.984 recall and 1.000 perfect which ensured zero false alarms and high operational reliability. Sensitivity analysis proved that the most dominating predictors are mud weight differential, mud weight as well as formation pressure as is consistent with the physics of well control. Future research ought to be done on the temporal modeling, field validation, uncertainty quantification, and integration of physics and machine learning.

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