Kick Detection and Influx Size Estimation during Offshore Drilling Operations using Deep Learning

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***Abstract*—An uncontrolled or unobserved influx or kick during drilling has the potential to induce a well blowout, one of the most harmful incidences during drilling both in regards to economic and environmental cost. Since kicks during drilling are serious risks, it is important to improve kick and loss detection performance and capabilities and to develop automatic flux detection methodology. There are clear patterns during a influx incident. However, due to complex processes and sparse instrumentation it is difficult to predict the behaviour of kicks or losses based on sensor data combined with physical models alone. Emerging technologies within Deep Learning are however quite adapt at picking up on, and quantifying, subtle patterns in time series given enough data. In this paper, a new model is developed using Long Short-Term Memory (LSTM), a Recurrent Deep Neural Network, for kick detection and influx size estimation during drilling operations. The proposed detection methodology is based on simulated drilling dataand involves detecting and quantifying the influx of fluids between fractured formations and the well bore. The results show that the proposed methods are effective both to detect and estimate the influx size during drilling operations, so that corrective actions can be taken before any major problem occurs.**

***Index Terms*—Kick detection, drilling, machine learning, influx estimation, deep learning, LSTM**

I. Introduction

During drilling operations, there are many events that can happen quickly and have large consequences related to the flow of drilling fluid in the well. One of these are a fluid influx, an intrusion of formation fluids (water, gas, oil or a combination of the three) into the well bore, often termed a "Kick". If it is not detected and counteracted in an early phase, the unstable effect can cause severe financial losses, environmental contamination and potentially loss of human lives. As such [1] concludes that; "Their prevention is undoubtedly the most important task in any drilling venture".

Recent experience indicates that in order to optimize the drilling operation the entire drilling system, not just the mechanics or software, needs to be designed from a control system point of view [2]–[7]. A difficult and expensive task for drilling rigs already in operations. Furthermore, model based detection in a well can be a challenging, both due to the very complex dynamics of the multiphase flow consisting of drilling mud, cuttings, reservoir fluids and modelling of subsurface conditions e.g pressure limits and formation friction.

A significant improvement of the performance of drilling operations can be obtained by hybrid systems. These can be designed based on a combination of historical data and simulated data to supplement areas of interests where historical data is sparse or unreliable.

In this paper, we present a new methodology that capitalizes on the improved and early kick detection. The proposed detection methodology is based on a flux-estimator, which involves detecting and identifying the flux of fluids between fractured formations and the wellbore. This estimator is based on the data driven machine learning method. To train the model a high fidelity drilling simulator, OpenLab Drilling, was used to generate pre-tagged data sets from a variety of drilling cases.

By utilizing a LSTM Neural network, readily available sensory data is analyzed to learn the dynamics of a well in order to detect a kick as early as possible. Corrective actions can then be taken before any major problem occurs. The simulation results show that the proposed methodology is effective to detect kick in the early phase during the actual drilling operation. It is demonstrated that the proposed methodology can reduce the cost associated with non-productive time through early detection and thereby prevent the risk of holes stability problems.

II. Drilling and well control

During drilling operations the circulation of mud trough the well serves many purposes, one of which is to keep the down hole pressure between the pore pressure and fracture pressure of the open hole reservoir to prevent loss of mud or influx. Due to uncertainties in the geological formation, one may drill into a reservoir section with an unexpected high pore pressure, such as a high-pressure gas pocket. If this pressure exceeds the annuls pressure a kick will occur. This kick has to be detected and acted upon by the crew members according to its size.

If the kick volume is larger then a certain threshold, the well needs to be shut in rapidly to stop further influx. The kick must then be circulated out in a controlled manner. On convectional drilling rigs this procedure, called well control, is a manual operation including sensor readings, calculations and control performed by several members of the drilling crew. It involves control of the blow-out preventer (BOP), the rig pump and the well control choke, all located at different locations at the rig. The well control choke is adjusted manually in order to maintain a certain pressure in the well. This may be a difficult task due to large time-delays in the drilling process and the complex behavior of the multiphase flow.

Reduction of false alarms and accurate information of the influx severity will in these cases increase the efficiency of the operation and the alertness of the crew.

III. Detection Algorithms for Conventional Drilling

A. Automated Monitoring of Traditional Parameters

The simplest approach to automated kick detection is to monitor the pit level or mud flow rate in and out of the well, and raise an alarm when threshold values are exceeded. Automated systems for monitoring variables such as pit levels and flow out would be able to spot reservoir influx in the same way as humans do today. However, one of the challenges with computer assisted decision making in drilling is that the active circulation system is a highly dynamic and complex system, and having alarms on simple rules would raise false alarms. Basically, the system needs to be able to understand what is going on and adapt to this information.

B. Detection of Wellbore Anomalies through Pressures

Another proposed method of detection of kick and loss, as well as other wellbore anomalies, is the use of standpipe pressure (SPP) and annulus discharge pressure (ADP). [8] The behavior of these pressures by themselves and in comparison to each other can help identify downhole problems. For kicks and losses, the alarms are based on pressure change equivalents for total flow or continuous total change in volume. Washout and plugging are detected based on changes in pressure. To reduce noise and make interpretation easier, variance is normalized.

C. Downhole Pressure Measurements

Measurements of downhole pressures may also be used for kick detection. These measurements can be transmitted to surface by traditional mud pulse telemetry, but real time measurements would then be limited to whenever the pumps are running. Data rate capabilities are limited, due to low bandwidth by mud pulse telemetry itself, and because other down hole data measurements is transmitted in the same way. A faster alternative is the wired drill pipe [9], which would also give measurements when not circulating.

D. Connection Flow-backs

Connected to the mud pit volumes are the flow-backs experienced during connections. During circulation, a certain amount of mud will be occupying the surface circulation system. When the pumps are shut off during a connection, this mud will flow back into the pits, increasing the pit level. Depending on the flow rate, the amount of flow-back should be more or less the same at each connection, and any changes may indicate changes downhole.

E. Return Flow

Monitoring the return flow out of the well may also provide indications of both reservoir influx and lost circulation. In a stable well, the flow in and out of the well should be approximately the same over shorter time ranges when flow rates are unchanged and a change from this will indicate unstable conditions.

In conclusion, the conventional kick and loss indications are summarized in [1] as follows: abnormal variations of active pit volume, difference between flow in and flow out, variations of standpipe pressure and annular discharge pressure, etc. It is widely accepted in the literature that flow measurements give the most rapid indication of a kick [10]. The flow-rate measurements are often quite noisy and subject to calibration problems. A gas kick alarm system is presented in [11] where the principle is to measure the propagation time of a pressure pulse through the well by using a sonic technique. A new drilling method was developed in [12], [13] by using the concept of micro-flux control, which is based on detecting a loss or influx of fluids, and instantly adjusting the return flow and the bottomhole pressure to regain control of the well.

IV. Detection Algorithms using Machine Learning

Machine learning is a field of computer science for pattern recognition and statistics. It is the scientific study of algorithms and statistical models that computer systems use to effectively perform a specific task without using explicit instructions, relying on models and inference instead. Machine learning algorithms build a mathematical model of sample data, known as "training data", in order to make predictions or decisions without being explicitly programmed to perform the task [14]. Machine learning algorithms are used in the applications of email filtering, detection of network intruders, and computer vision, where it is infeasible to develop an algorithm of specific instructions for performing the task. Machine learning is closely related to computational statistics, which focuses on making predictions using computers. As the complexity of the models have increased the later years it has become evident that the quality of the input data to machine learning models plays a significant impact on their performance [15]

Machine learning methods have been investigated for kick detection recently [16], [17]. They also provide a good overview of the role of machine learning and a summary of state-of-the-art, i.e. artificial intelligence, for drilling applications. In [18], machine learning algorithms were applied for detection of well control events for a case study. In [19], a case study in Iranian oil fields was conducted for early kick detection using real-time data analysis with dynamic neural network.

V. Proposed Algorithm

Deep learning is subset of machine learning methods. Deep learning architectures such as deep neural networks, recurrent neural networks, and deep belief networks can have hundreds of millions of parameters [15], [20], allowing them to model complex functions such as nonlinear dynamics. Unlike many machine learning methods, they do not require a human expert to hand-engineer feature vectors from sensor data. Some deep learning models can, however, present particular challenges in physical robotic systems, where generating training data is generally expensive, and sub-optimal performance in training poses a danger in some applications. Yet, despite such challenges, researchers are finding creative alternatives, such as leveraging training data via digital manipulation, simulation and automating training to improve the performance of deep learning models and reduce the training time.

Compared with traditional neural networks, recurrent neural networks (RNNs) are known for making decisions by reasoning about previous events. The looping nature of RNNs allows information to persist so that not only the information from the previous time step and current time step model the prediction, but also the information from more than one previous time steps. Some of the applications that can be successfully solved with RNN are language modeling, speech recognition, image captioning, and translation.

Depending on the application, it varies how much of the historical data is needed to be taken into account. Standard RNNs do not perform well when much context is needed. This is dubbed the long-term dependency problem.

Considering the above issue with the standard RNNs, in this research, we utilize a special kind of RNN i.e. Long Short Term Memory (LSTM) networks. The selected approach is capable of learning long-term dependencies. Instead of the chain of repeating simple modules having a single neural network layer in standard RNNs, modules in LSTM have a more advanced structure having four neural network layers.

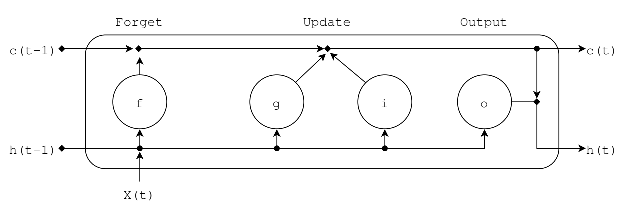


Fig. 1: LSTM module

These four layers in an LSTM module perform different tasks during the training phase. Three of them act as gates which optionally let information through and are made of a sigmoid neural net layer. Therefore the output of these gates is a value between 0 and 1 i.e. value 0 let nothing through and value 1 let everything through. First, the forget gate layer, f in Fig. 1, decides which information should be removed by looking at the current input, x(t) to the module and the output from the previous module, h(t-1). Then, the input gate layer (g) and the tanh layer (i) collectively decide which new information should be added to the existing knowledge, c(t). Once we are done with the updating of information within the module, output gate layer (o) decides what to output, basically a filtered version of the existing information.

VI. Case studies

The proposed methodology is evaluated on a high fidelity drilling simulator-OpenLab from NORCE. OpenLab was used to generate 5781 random drilling cases with 10 minutes of data, where 29% of the simulations contained influx, 5% contained mud loss and 0.6% experienced simultaneous loss and influx. The data was divided into three groups, where 70% was used to train the network, 10% for validation during training and 20% was reserved for testing the trained model. To more easily be able to compare methods, the data sets was divided globally, so all networks and tests can use the same data for training, validation and testing.

Due to current limitations in the simulation software the regression networks have been trained on finding the influx mass rate. While this is presumed to be viable in the simulated cases where the influx substance is predefined, this is an unrealistic achievement in a real environment as the influx substances is unknown. Training on the mass rate of a known substance will however indicate if its possible to estimate the volumetric flow rate of an influx.

For this paper low frequency data sampling at 1Hz with no noise has been used to train the model. With the low data sampling rate the network will have difficulties in picking up on subtle patterns like sonic waves or pressure pulses which can move at the speed of sound. However at 1Hz the lack of noise in the data is more comparable to real drilling data as much of this can be filtered out over this time span.

A. Data Selection

In order to generalize the network, counteract over-fitting and challenge the model on dynamic scenarios where traditional methods are more prone to error, several aspects of the simulations where randomized within a set operation range.

1) Influx simulation: OpenLab has the ability to simulate well operations with both artificial and geopressure based influx. During the artificial influx simulations an pre-defined influx is injected into the well at a predetermined depth, rate and total influx mass. Being independent of the drilling operations these cases should only be detectable from the well response and not as a consequence of how the well is operated.

Geopressure based influx or loss is based on a near-well formation flow model that calculates the flux between the well and the formation. The influx or mud loss is determined by the pressure difference between well and formation, the permeability, the porosity, and the density of the drilling fluid. This makes it difficult to reliably simulate a given realistic influx without introducing clear engineered operation patterns for a network to pick up on. To counteract this several different formation models, initial mud density and flow patterns where used and run dynamically using randomized patterns. With the large sample size, geopressure based influx inevitably occurred.

In the final data set 57% of the influx scenarios were artificially based and 43% geopressure based. All cases were represented in the Training, Validation and Testing sets.

2) Geology and mud density: The geological profile determines the location of the kick and the influx- / loss- rate in the simulation. To help generalize the model five different pressure profiles were designed. The geopressure properties of the profiles were not changed. Fig. 2 represent a example of the profiles used. Variations here included peaks in the fracture area to decrease the exposed areas and shifts in the Specific gravity (SG) range.

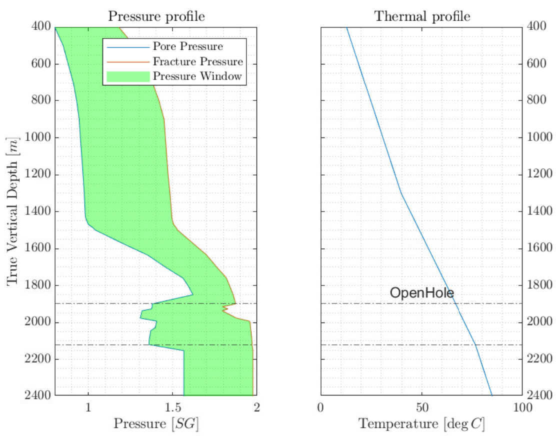


Fig. 2: Example of geological profile

To initialize the well in different pressure zones of the geological profile, each profile was used in several cases with a different initial mud density in the well. With these variations a total of 26 different initial wells were used, and the simulation algorithm randomly selected one at the start of each simulation. To increase the chance of influx based on lower annulus pressure then the geopressure profile, profiles with increased chance of influx were represented more often. 14 of the 26 profiles produced geopressure based influx in the final data set. All were represented with artificial influx.

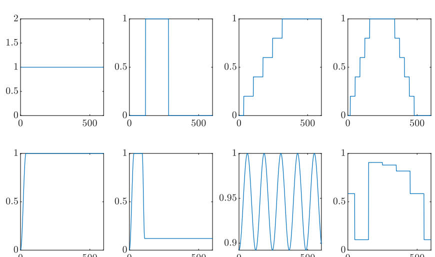


Fig. 3: Example of randomly seeded flow profiles

3) Flow Rate: The mud pump (flow in) rate was varied trough the simulations both to teach the network the response of a well during operations and to induce geopressure based influx / mud loss from the resulting pressure changes in the well. The initial maximum flow rate of each simulation where randomly selected for each simulation, favoring a higher flow rate, by eq 1. This to increase the pool of actively driven wells in the data sett. Furthermore, a variety of flow patterns were designed as a scalar on Q_{flow} to operate the flow during a simulation, Fig. 3. The design parameters of each pattern were seeded by a random value, ex number of periods and amplitude in the sin curve.

$$Q_{flow} = (1 - U([0,1]))^2 \cdot Q_{max} \tag{1}$$

4) Choke opening: The choke opening was randomly initialized by eq 2. Heavily favoring a large choke opening but allowing for some simulations to be run with a restricted choke to induce mud loss and further vary the data set.

$$C_{opening} = 0.98 \cdot (1 - U([0,1])^5) \tag{2}$$

B. Training and Test Data set Selection

The raw data from the simulations operate on severely different scales, with pressure values being on the scale of 10^7 and flow rates being scaled to 10^{-3}. This large difference of scale posed a problem for training the network. To solve this the standard score was calculated on the data set. (eq 3)

$$z = \frac{x - \mu}{\sigma} \tag{3}$$

Where μ equals the mean and σ equals the standard deviation of the sensor value x over the entire data set.

For this paper, three different sets of sensor data was evaluated, as shown in table I. In set A, traditional flow data is combined with pressure data: the choke opening and bit depth will have a direct impact on the relating choke and bit pressure. To allow the network to pick up on pressure and flow abnormalities resulting from changes in these values they where included in the training set.

In set B only flow rate data were used to see if a DNN can improve on traditional methods given the same data, and to evaluate the impact of adding the extra sensors in set A. While Set C was used to compare the result given only Pressure related data.

Sensor	A	B	C
Flow rate in	I	I	-
Flow rate out	I	I	-
Stand pipe Pressure	I	-	I
Choke Pressure	I	-	I
Choke Opening	I	-	I
Bit Pressure	I	-	I
Bit Depth	I	-	I
Influx mass rate [kg/s]	O	O	O

TABLE I: Sensors used in networks, I: Input, O: Output

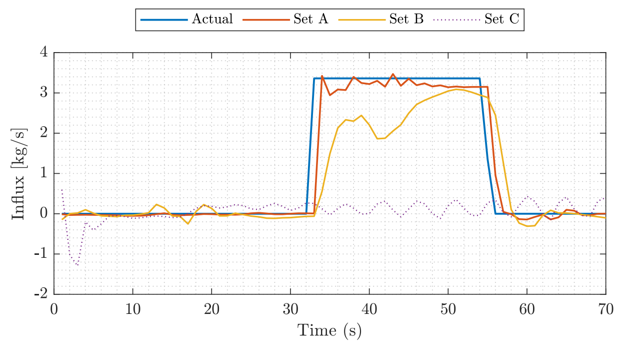
C. Classification network

A influx classification method was tested both by training a LSTM classification network and by tuning a trigger value on the regression network. While the classification network may prove efficient, it has the disadvantage of having to be retrained if we want to tune its sensitivity. Meanwhile a limit on the predicted influx may prove beneficial as it allows for real time tuning of the network sensitivity. This method could also be compatible with the advantages of adaptive alarms found in [18]

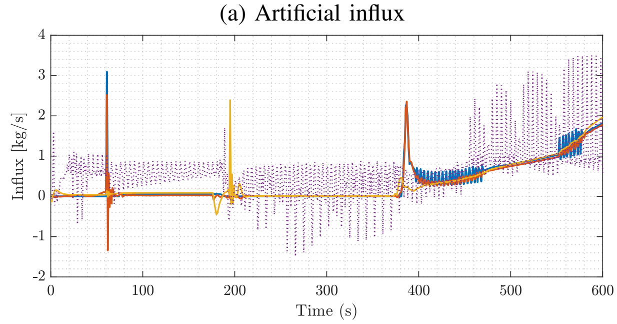
VII. Results

A. Regression

Figure 4a and 4b shows the prediction of the models one a selected artificial and geothermal influx case from the test set which has not been shown to the model during training or validation. From the figures we clearly see that set A preforms most accurately in both cases by closely matching the actual influx. While in 4a it suffers from a 1s lag in the prediction it closely follow the actual influx real time in the geopressure based simulation, fig 4b, As with set B and C it misses out on the small georessure based influx of 0.058kg/s spanning from ∼75s to ∼195s mark. Set B takes some time to build up towards the artificial influx and the last geopressure based influx while it also misses the first peak during the geothermal influx, and experience a false positive around the∼195s mark, this correlates to the mud pump being turned on in this simulation. The model trained on set C shows no apparent detection of the artificial influx, and although there seems to be some correlation between the influx rate and the prediction in the geopressure based case it is apparent that the pressure sensor data by itself makes for an unreliable model in this case.



(a) Artificial influx



(b) Geopressure based influx

Fig. 4: Prediction of influx mass rate. Where the blue line represents the simulated influx rate, and set A, B & C reprecents the predicted responces

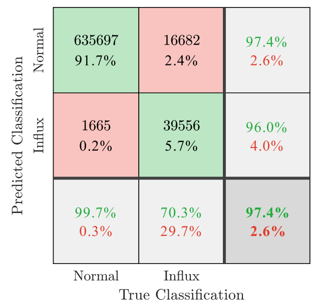
Examining the best preforming model, set A, on the whole test set we achieve a root mean square error (RMSE) of 0.10 kg/s influx mass rate on the test set of the total data set. Further analyzing the test data shows that a larger part of this error comes from some uncertainty during an influx, with a RMSE of 0.34 kg/s, while it tends to be smaller during stable operations, with a RMSE of 0.04 kg/s.

The results demonstrate the effectiveness of the proposed method and show that it can effectively detect a kick in the early phases of the influx. This concludes that the proposed method can increase influx rate prediction accuracy and reduce the need for rig modifications, specialized equipment and advanced physics based models to detect discrepancies during operations.

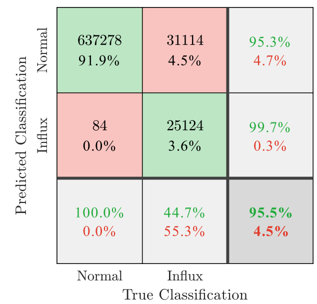
B. Classification

In fig. 5, accuracy and loss of the different influx classification methods are shown. 5a and 5b reflects different trigger values on the classification of an influx on the predicted influx rate. While 5a uses a lower trigger value to reduce false negatives, and the total loss, 5b almost completely eliminates false positives by increasing the trigger value and accepting a larger total loss on the influx classification. The limit used on 5b was 0.97 kg/s while 5a used a limit of 0.13 kg/s.

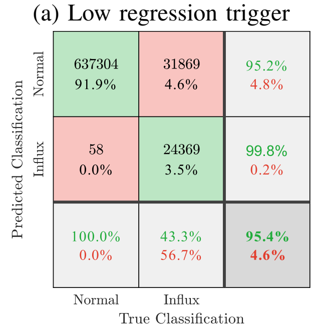
The results from the LSTM classification network are shown in 5c, and preforms similar to a regression network tuned to reduce the number of false positives. In fig. 5d influxes were classified purely by a trigger value on flow rate deviation between Flow in and Flow out of the well, where the threshold was giving a best case scenario of being optimized on the minimum loss for the given test set. All classification methods presented using DNN's out preformed the traditional best case scenario. With the best network giving a ×2.5 improvement.



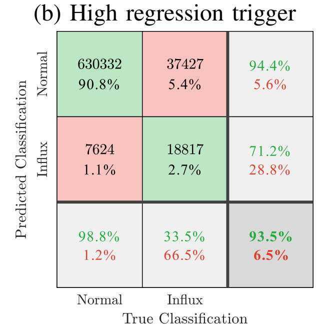
(a) Low regression trigger



(b) High regression trigger



(c) Classification Network

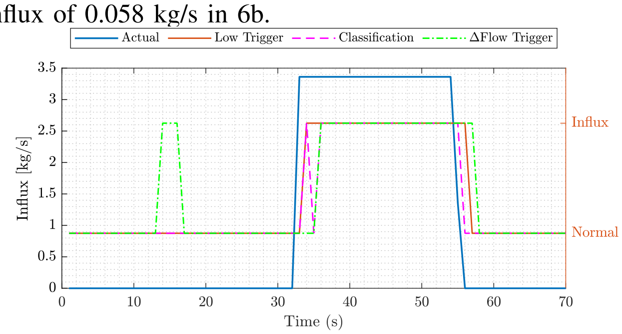


(d) ΔFlow trigger

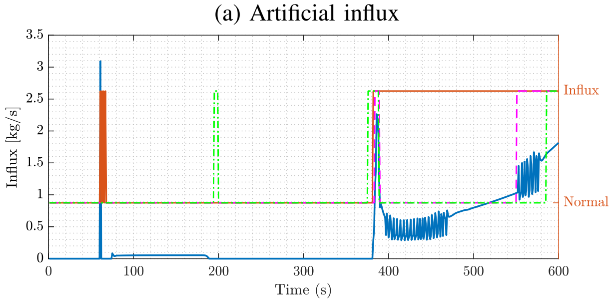
Fig. 5: Classification results the whole test set. The sum of the whole numbers in the columns represent the number of occurrences in the simulation test set and the sum of the rows represent the number of occurrences predicted by the network. Green squares represent correct classifications and red squares represents false classifications.

Fig. 6a and 6b Compares the different influx classification methods on both the artificial influx and the geopressure based influx. The results show that the ΔFlow trigger is prone to errors. The false positive at 15s mark in fig. 6a and 195s mark in fig. 6b both correlate to the mud flow into the well being ramped up. The apparent early influx indication around the 375s mark in fig. 3 correlates to the mud flow shutdown in this scenario. During the artificial influx it suffers from a 3 second lag in both the start and end of the influx.

The LSTM Classification network is unstable during the start of the artificial influx, first detecting it at a 1s delay and then achieving a stable detecting after 3s delay, giving a mild improvement on the ΔFlow method. It detects the end at a 1s delay, better then both the other methods. For the geopressure based influx it also improves on the ΔFlow method with no false positives. However it misses out on much of the main influx at the end. Detecting the first peak after 2 seconds, and then giving a false negative as soon as the influx rate reach below 1kg/s and not detecting it again before it builds up to more than 1kg/s. The trigger on the predicted influx rate experience a 1s lag at the start of the artificial influx and 2s lag at the end. It's the only one to pick up the peak in the beginning of the geopressure influx, but suffers from some noise afterwards. It correctly identify the last influx in 6b with no lag. None of the methods were able to pick up on the small influx of 0.058 kg/s in 6b.



(a) Artificial influx



(b) Geopressure based influx

Fig. 6: Kick classification. Where the blue line represents the simulated influx rate on the left axis and the remaining lines is the binary classification of influx or no influx on the right axis

VIII. Conclusion

In this paper, we develop a methodology for detection of an unexpected influx during drilling operations. The proposed detection methodology is based on a flux estimator, which involves detecting and identifying the flux of fluids between permeable or fractured formations and the wellbore. A new model is developed using deep learning algorithms to better detect kick and estimate the rate of influx in the well, based on readily available sensory data from the drill rig. The results demonstrate the effectiveness of the proposed method and show that it can effectively detect a kick in the early phases of the influx. The proposed method can increase kick detection accuracy and reduce the need for rig modifications, specialized equipment and advanced physics based models to detect discrepancies during operations. The results show that the proposed methods are effective to detect and identify the unexpected kick during drilling operations, so that corrective actions can be taken before any major problem occurs, benefiting both safety and operation costs.

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