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Improving Gas Well Economics with Intelligent Plunger Lift Techniques

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Abstract. In this paper, we present an approach to reducing bottom hole plunger dwell time for artificial lift systems. Lift systems are used in a process to remove contaminants from a natural gas well. A plunger is a mechanical device used to deliquefy natural gas wells by removing contaminants in the form of water, oil, wax, and sand from the wellbore. These contaminants decrease bottom-hole pressure which in turn hampers gas production by forming a physical barrier within the well tubing. As the plunger descends through the well it emits sounds which are recorded at the surface by an echo-meter that measures tubing acoustics. We analyze acoustic time series data to determine when the plunger comes to rest at the well bottom. By using the Pruned Exact Linear Time (PELT) algorithm for change point detection and k-means clustering to identify points when the plunger passes a pipe collar, we are able to determine the exact time when the plunger reaches the bottom of the well with a 98% accuracy. By knowing exactly when the plunger reaches the well bottom, operators can reduce plunger dwell time resulting in improved well production.

Keywords: Change Point Detection, Artificial Lift System, Gas Well, Time Series, k-means Clustering, PELT.

1 Introduction

There are approximately 900,000 active gas well in the United States (U.S.) [1]. Technological advances since 2010 have created a boom and glut of reliable and affordable energy that has boosted economies of typically rural towns from the Dakotas to Texas and all through Appalachia. Conversely, despite U.S. national production being at possibly an all-time high, deep geological gas deposits have started to decline.

Natural gas producers are constantly innovating in order to maximize productivity by efficiently extracting the entire gas resource in the minimum time frame. Historically, wells have been drilled vertically – but the aforementioned boom since 2010 has seen a rise in unconventional horizontal wells. The techniques discussed in this paper focus on horizonal wells but can be easily extended to vertical wells with no modifications. Gas production will naturally decline due to age, owing to bottom-hole pressure depletion as a function of time; a major contributing factor.

The build-up of liquid and sand, also known as contaminants, is another contributing factor to clogging the well and reducing production. As pressure decreases, contaminants begin to form at the bottom of the well and fill the wellbore. This problem is known as liquid loading where the gas pressure is not high enough to lift contaminants to the surface and out of the well. It is basically the inability of the gas to remove liquids being produced in the wellbore. These contaminants hinder the production process and need to be removed from the wellbore. If undealt with, the liquid will continue to form creating a static column of liquid that acts as a plug blocking the well and eventually ceasing well production.

Successful removal of the contaminants may return the well back to its natural production decline levels, but one can never expect it to the return to initial levels experienced when first brought into production (a natural consequence of well aging). A plunger lift system is used to remove the well contaminants. A plunger travels through the well until it reaches the bottom of the well. The lift system then lifts the plunger up through the well during which time the plunger removes the well contaminants. The well does not produce while the plunger is within the well. It is, therefore, important to minimize the total time the plunger is within the well. The primary plunger time components are the travel time through the well to the bottom, bottom dwell time, and the travel time through the well to the top. The travel times are variable, depending on the length of the wellbore and the amount of contaminants within the well. And, these travel times cannot be impacted through outside intervention. However, the dwell time at the bottom of the well can be minimized if the time at which the plunger reaches the bottom can be detected accurately.

This study sets out to improve natural gas production by reducing the bottom-hole dwell time of a plunger, a mechanical solution to the liquid loading problem of accelerated production decline once contaminants form within the wellbore. There are a number of approaches to dealing with liquid loading for example, Khamehchi *et al*. [2] adopt a different approach to improving production efficiency by exploring better prediction of liquid loading by presenting an artificial neural network model for predicting the minimum flow rate for continuous removal of liquids from the wellbore. Veeken and Belfroid [3] offer a new perspective on gas well liquid loading and unloading by challenging the conventional idea of droplet flow reversal, presented initially by Turner in 1969. They explore methods of tubing wall modification via small-scale lab testing and present a method of hydrophobic coating of the tubing to reduce gas rate to below the level in which liquid loading occurs by approximately 50%.

In order to determine ways to reduce the dwell time, our research leverages the change point detection algorithm which detects changes in the mean and variance of time series data and the k-means clustering to detect the individual collars.

The results of the change point detection illustrates that the PELT (Pruned Exact Linear Time) algorithm is able to detect the collars and calculate the time the plunger passes each collar and starts traveling though fluid. The results from k-means identifies the collars and other unique sounds in the tubing acoustic.

The remainder of this paper is organized as follows. We review the plunger lift system in Section 2. We present our data characteristics in Section 3. In Section 4, we present our methodology and analysis of the data. We review the K-means clustering approach in Section 5, and we present our results and analysis thereof in Section 6. We examine some related ethical issues in Section 7 and draw the relevant conclusions in Section 8.

2 Plunger Lift System

A plunger lift system, which is also known as an artificial lift system, is a mechanism used to remove contaminants that form in the wellbore. Examples of the contaminants are water, oil, sand, and wax. It is an efficient way to operate because it returns the well to near full production by restoring low pressure to the wellbore. When the well is producing, the plunger is resting at the surface and the valve that lets fluid out of the well is open. When contaminants start forming in the wellbore, the valve is closed, which stops the flow and shuts in the well. The plunger is then released descending to the bottom until it reaches the bottom hole assembly. As soon as the well is shut in, pressure starts building in the casing and tubing. When pressure is at optimal levels, the valve is opened, and the plunger returns to the surface pushing the fluids that have built up in the wellbore, essentially clearing the well of contaminants and restoring production. This cycle repeats itself many times until production is restored back to natural decline levels, see Figure 1.

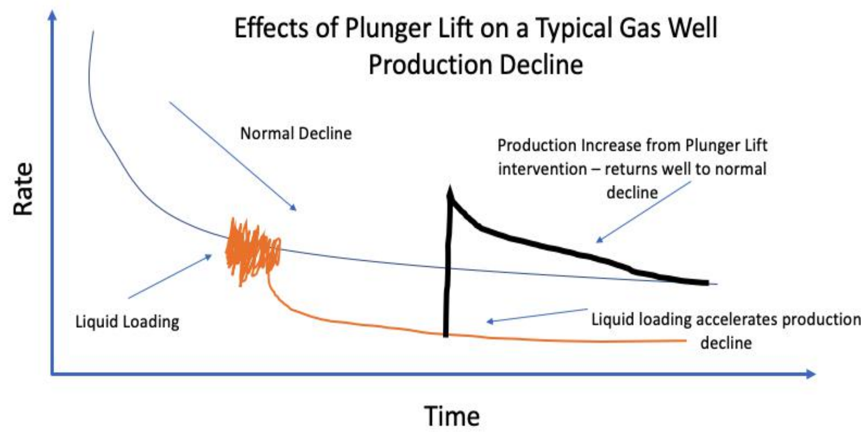

Fig. 1. Natural Production Decline in a natural gas well.

The idle time of a plunger at the bottom of the wellbore reduces production of gas from aging wells. The accumulation of pressure at the wellbore diminishes with age, as the plunger lift system drops with the effect of gravity through the well, the pressure at the wellbore increases, the higher the pressure the greater the assistance during the suction phase, the primary method of gas extraction from the well. With time, the naturally occurring pressure diminishes with usage resulting in a reduction in well productivity and increased idle time at the bottom of the wellbore. It is common practice to not wait for the liquid loading problem to affect production, it's generally prudent to lift contaminants before the problem begins. Engineers apply the Turner, Coleman equations [4] to determine an estimated gas velocity required to prevent a drop of liquid from falling. They help to determine the minimum gas velocity, also known as the unloading velocity, required to avoid liquid loading.

There are a number of collars, see Figure 2, in the wellbore that are used to the join sections of tubing together. When the plunger passes each collar, it appears to emit a specific frequency, which helps to determine the plunger location and subsequent arrival at the bottom of the well. Additionally, another level of complexity added to the problem has to do with the plunger traveling through fluid to rest on the spring on the bottom hole assembly. Once the plunger starts traveling through fluid that has accumulated in the wellbore, it will be difficult to read the collars due to the change in acoustic frequency as the plunger transitions from a hollow tube filled with air to one filled with water and other contaminants.

Fig. 2. Example of a natural gas well collar joint (highlighted in blue). Picture by Atsu Atakpa, 2018.

We implemented a change point detection algorithm to analyze tubing acoustic data; examining for differences in the mean and variance of the tubing acoustic frequency. Potentially these changes might be related to the plunger passing a collar or arriving at rest on the bottom hole assembly.

3 Data

The tubing pressure, tubing acoustic and casing pressure data used in this research was provided by the production engineering department of an undisclosed research partner**.** This data was captured and recorded using an echo-meter and provided as text files. The echo-meter is directly connected to the wellhead and the reading from the echo-meter recorded and saved on a computer. Because the data provided were for multiple wells, we created a database using Microsoft SQL Server to store the data for easy extraction and analysis. Initial evaluation of the data found that there were not any missing records in the dataset provided. There were over 10,000 records for each plunger lift cycle.

The basic data set information is summarized in Table 1. In Table 2, we present the basic statistics for the natural gas well plunger data.

Table 1. Basic Dataset Variable Information.

Variable	Type	Description	Units
Elapsed Time	Float	The time in nanoseconds since the plunger lift operation began	Nano-seconds
Tubing Acoustic	Float	Acoustic recording measured in Hertz	Hertz
Tubing Pressure	Float	Time series pressure recording within tubing	PSI
Casing Pressure	Float	Time series pressure recording within casing	PSI

Table 2. Basic Statistics for Well Plunger Lift Data.

Elapsed Time	Tubing Acoustic	Tubing Pressure	Casing Pressure
Min. : 0.017	Min. :-0.6567990	Min. :157.2	Min. :232.4
1st Qu.:1432.429	1st Qu.:-0.0011280	1st Qu.:175.4	1st Qu.:242.3
Median :2864.842	Median : 0.0000290	Median :237.1	Median :283.5
Mean :2864.842	Mean : 0.0000192	Mean :224.9	Mean :276.3
3rd Qu.:4297.254	3rd Qu.: 0.0012510	3rd Qu.:271.7	3rd Qu.:304.9
Max. :5729.667	Max. : 1.1191770	Max. :287.5	Max. :316.0

Exploratory data analysis gives us an overview of how our data is structured, as well as an initial ideal or normality in our data. The mean and median for each variable shows differences in measurement.

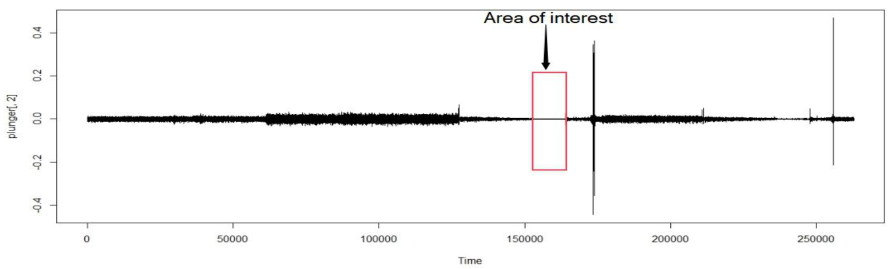

Fig. 3. Initial data including valve closed, plunger at rest, and plunger travel up the well.

The data that was provided was too large of a scope for us to use to predict when the plunger reaches the bottom of the well. The initial data included when the valve was closed, when the plunger was at rest at the top of the well, and when the plunger was traveling back to the surface as shown in Figure 3. This is an issue, especially true when we attempt to use a change point detection algorithm, because the mean and the variance of such a large dataset will not be a good measure to detect such a small change point for when the plunger comes to rest.

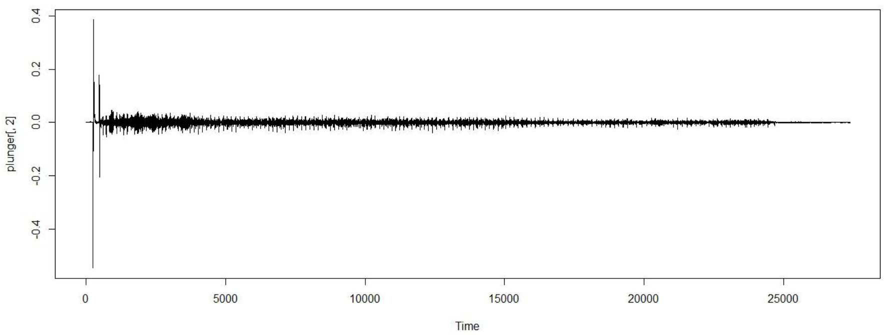

Fig. 4. Data sample for closed valve and plunger travel to bottom of well.

New samples were then collected for only when the valve was closed and the plunger is dropped to the bottom of the well as shown in Figure 4. Conducting exploratory data analysis on the new dataset showed there will not be an issue with the size of the dataset nor with the mean and variance as this is key when using change point detection.

4 Methodology and Analysis

We implemented and evaluated the three most widely used change point detection techniques [5]: 1) the binary segmentation algorithm, 2) the segment neighbor-hood algorithm, and 3) the Pruned Exact Linear Time (PELT) algorithm. These techniques utilize a minimization approach utilizing Equation 1.

$$\sum_{i=1}^{m+1} [C(y_{(\tau_{i-1}+1)\tau_i}) + \beta f(m)] \tag{1}$$

Where *C* is a cost function for a segment and the penalty to prevent over fitting is *f(m)*.

Change point detection is a field of statistics that deals with estimating a point at which statistical properties of a subsequent observation change. Each change point location is represented by an integer of between *n* and *n-1* following a probability distribution of time series changes. Where change points are suspected, a test statistic is applied to validate the null hypothesis that no change point is detected vs. the alternative that a change point is detected.

Binary segmentation applies a single change point test statistic to the entire dataset. If a change point is detected, then the dataset is split in two the location of detection, producing two new datasets. The detection processes are repeated on the two new datasets and if new change points are detected the datasets is split further. This repeats until no new change points are identified.

Without the presence of any missing data, the analysis was conducted by first performing some exploratory data analysis. We plotted the data to confirm that the data was in a time series format. Additionally, we confirmed that there was visual evidence of changes in the data. Parameters were set for both the binary segmentation and segmented neighborhood for changes in mean and variance. There was only one detected change point. Figure 5 illustrates the binary segmentation identifying the one singular change point.

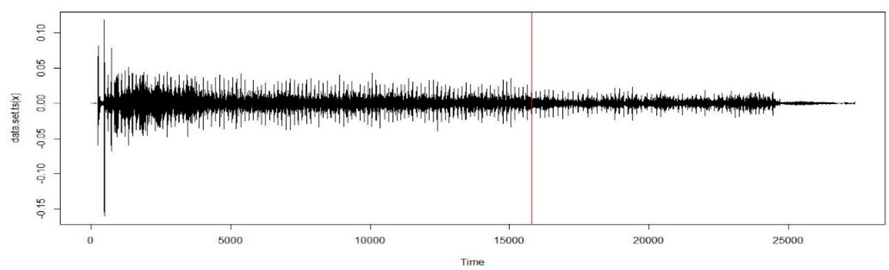

Fig. 5. Plot of a single change point using binary segmentation.

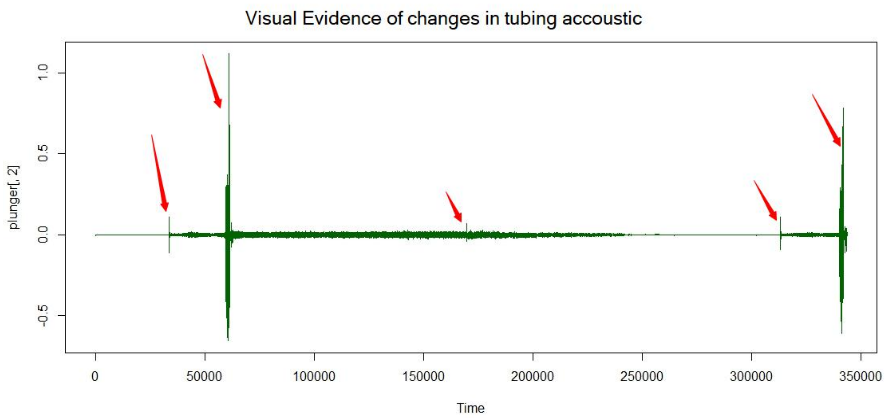

Fig. 6. Plot of multiple change points identified using PELT.

We expand our analysis and use the Pruned Exact Linear Time (PELT) algorithm with the data segmented to the point where the well was shut in and the plunger begins to fall. We set the parameters for the algorithm as finding changes in mean and variance. The PELT algorithm was able to identify the individual collars in the data as shown in Figure 6. See Figure 7, which shows the detailed results from the PELT algorithm. Each collar was detected at points where the plunger was not traveling through fluid and the point where it starts traveling through fluid, and eventually comes to rest.

Evaluation of the visual evidence confirmed that the algorithm was able to detect the collars. By using visual tools such as "plotly", we were able to zoom in and visually inspect the results of the PELT algorithm.

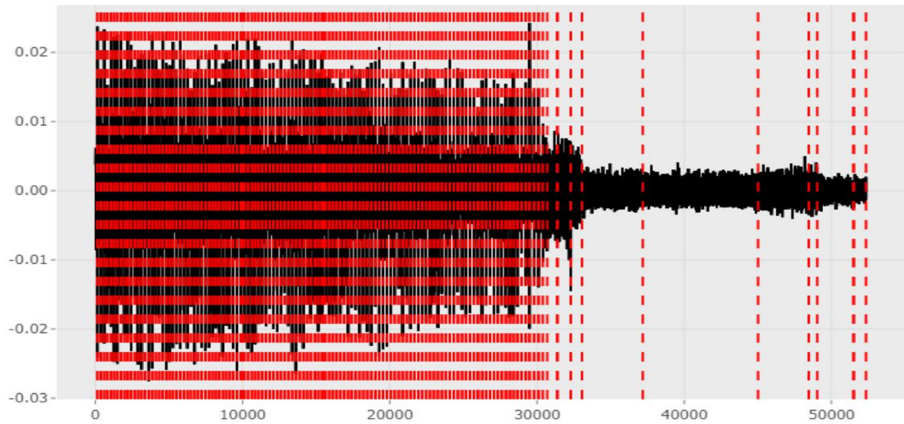

Fig. 7. PELT (Pruned Exact Linear Time) identification of change points (the dashed vertical lines)

We further explore different machine learning algorithm in the form of k-means clustering for more insights

5 K-Means Clustering

K-means clustering [7], an efficient unsupervised machine learning technique, is employed to find interesting patterns in our dataset. Clusters are an unlabeled data point, which share similar attributes that are grouped together. The number of centroids, or groups, are denoted by k. In other words, the number of centroids that we intend on finding are labeled as "k". We explore this algorithm, which focuses on grouping elements of the same structure, and use it to identify the collars in the dataset. Illustrated in Figure 8 is a scatter plot diagram of the data points for the tubing acoustic measurements.

One of the challenges associated with the k-means algorithm is the determination of the value to use as k. The elbow method is often used to determine the k value included in the algorithm. The elbow method uses the algorithm on a range of k values (e.g. 1-10) and computes the average score for each k in all the clusters. By setting the value of k to two, we identified two clusters of sound levels that were vibrating at unique frequencies. However, visual inspections suggest that we have more than two clusters in the data. Figure 9 shows the results of k-means with k being two.

We used different k values to improve our initial results. This particular well had 159 collars. The algorithm was able to identify each of those collars when we set the *k* value to eight.

The number of elements in each cluster is shown in see Figure 10. Cluster 3, which has the greatest number of elements identified to be in that cluster, is a depiction of the sound that was vibrating at a low frequency hence clustered as one. It is the period of silence after the plunger passes a collar. Within the time the plunger passes each collar, there is a period of silence, which is captured and identified in cluster 3. Cluster 1 is the cluster of interest to us. We found 159 observations in that cluster, representing the individual number of collars known. Other clusters identified in the tubing acoustic are unknown, but were picked up by the echo-meter.

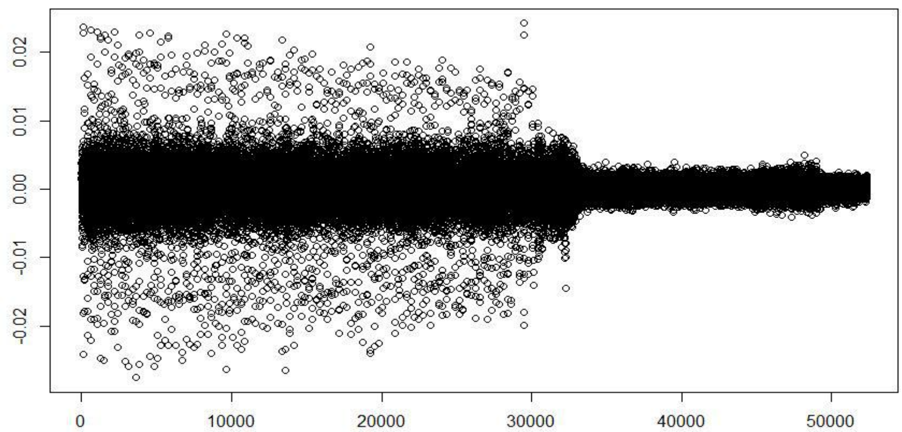

Fig. 8. Scatter plot of plunger lift acoustics.

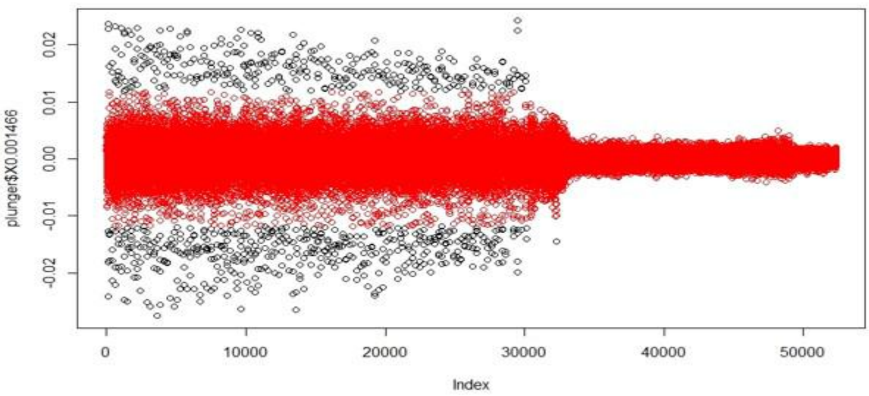

Fig. 9. Scatter plot of plunger lift acoustics with two clusters (one red, one black) identified using k-means clustering with k=2.

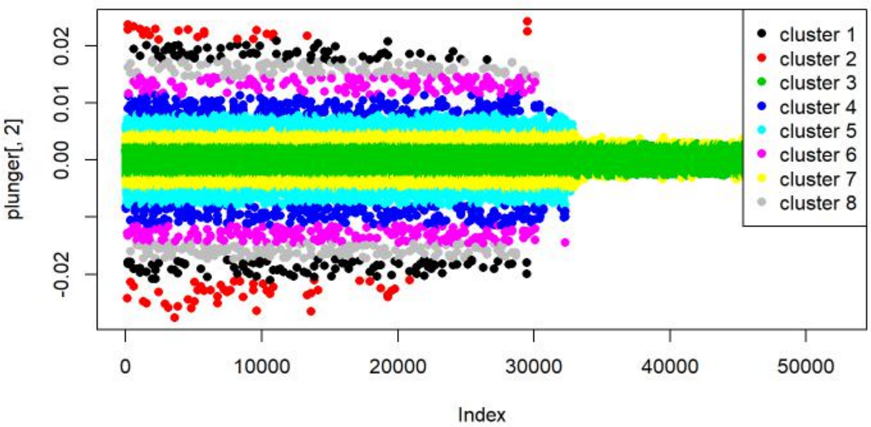

Fig. 10. Scatter plot of plunger lift acoustics with eight clusters identified using k-means clustering with k=8.

6 Results

The results from binary segmentation and the segmented neighborhood were very similar. They segmented the data into two where there was a distinct change in mean and variance. However, the two algorithms were not able to detect the collars. Additionally, the two algorithms do not perform well with noisy data.

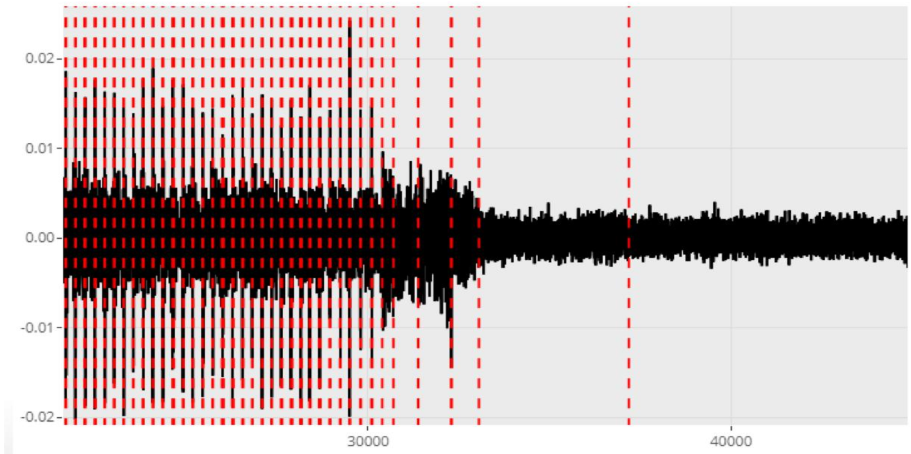

Fig. 11. Detected change points using PELT.

The PELT algorithm, however, performed very well when applied to the cleaned dataset. It detected each collar as shown in Figure 11 and Figure 12. It also identified the point at which the plunger starts traveling through fluid, as well as the point at which it eventually comes to rest. For this dataset, it identified 257 change points. The red vertical lines are the individual change point identified by the PELT algorithm. The black lines are the tubing acoustics. A zoomed in version of the PELT algorithm detecting the collars is shown in Figure 12.

Additionally, we were able to determine the exact time the change points occurred, along with the tubing pressure and casing pressure. These exact readings will be essential when working with streaming data. The image below shows the elapsed time, tubing pressure and the tubing acoustic data at the point where the PELT algorithm detected changes in mean and variance. The timing is summarized in Table 3.

The goodness of fit, which measures how well our model performed, when fit to a set of observations was 75.7 percent with a k value of 2 as summarized in Table 4. The goodness of fit is a ratio of the sum of square and total sum of squares. The sum of squares is the addition of the square of variations for the observations. It measures the deviation or variation of the observations from the mean. The results when k is 2 suggests that we have more than two clusters in the data.

After application of different values for k, the results when k is 8 can be seen in Table 5. The success of the t measure is 97.8 percent, see Table 5. The algorithm was able to group the collars in one cluster and identify other sound levels present in our data.

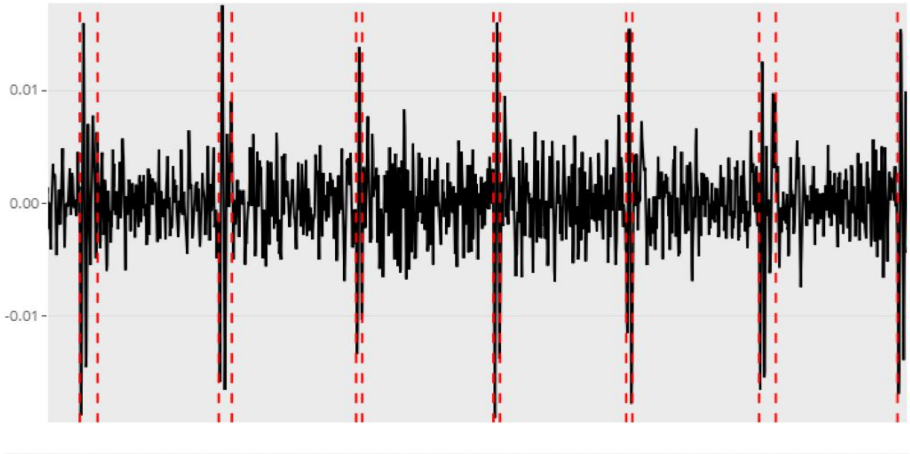

Fig. 12. Detected collars using PELT.

Table 3. Table of multiple change points detected.

Index	Elapsed Time (sec)	Tubing Acoustic	Tubing Pressure
141	304.7	-0.00202	400.496613
153	305.1	-0.013257	400.71701
368	312.266667	-0.001628	400.979401
379	312.633333	-0.010462	401.220764
594	319.8	-0.000219	401.357208
605	320.166667	-0.01271	401.430664
825	327.5	-0.001533	401.850464
837	327.9	-0.00498	402.02887
1050	335	-0.002294	402.112823
1060	335.333333	-0.014988	402.364716
1275	342.5	0.002695	402.501129
1286	342.866667	-0.010621	402.742523
1507	350.233333	0.000914	402.931427
1518	350.6	-0.015476	403.225281
1738	357.933333	-0.004635	403.435181
1751	358.366667	-0.014122	403.655579
1968	365.6	-0.001623	403.760529
1979	365.966667	-0.010731	403.886444

Table 4. K-means clustering results for k=2

Goodness of fit	Cluster Size		Tubing Pressure	
75.70%	1	768	1	2.731
	2	51582	2	5.946

Table 5. K-means clustering results for k=8

Goodness of fit	Cluster Size		Tubing Pressure	
97.80%	1	159	1	1.66E-06
	2	266	2	1.44E-05
	3	72	3	3.79E-05
	4	308	4	8.89E-05
	5	494	5	0.000172
	6	7431	6	0.000254
	7	41460	7	0.000353
	8	2160	8	0.000529

7 Ethics

Mining for natural resources, is an industrial process that has effects on the environmental and populations in the area of the development. Mining firms deploy techniques to maximize the potential from existing wells in-order to limit the impact and costs associated with exploring and tapping new energy resources.

The techniques in this paper cannot claim to improve all plunger lift systems at every location. In conjunction with existing methods, there is potential to limit the impact of natural gas extraction by improving the plunger lift operation. By extracting the maximum yield possible with each iteration of the extraction process and subsequently limiting the time a well is operational.

The cost of implementing a poor model would be catastrophic to both the gas well and our pursuit of energy resources. Failure to effectively deal with the liquid loading problem due to poorly predicting the most optimal dwell time that plunger rests at the bottom of the well while pressures build up to acceptable levels to ensure the total return of the plunger lift and all contaminants will eventually cause production to decline and prematurely kill the well.

8 Conclusions

Wells that are on a plunger lift assist go through multiple cycles. Recording the data for each cycle and determining when the plunger is at the bottom of the well is a very difficult task. This process requires having an employee physically present at each location recording the data, which could be difficult given the remote locations of many of these wells. For this project we were able to use algorithms to determine points where there were changes occurring in the tubing acoustic data that will assist us in predicting when the plunger is at rest. When using the change point algorithm, specifically the Pruned Exact Linear Time (PELT), changes in the mean and variance as the plunger travels past each collar is key to the determination of when it reaches the bottom of the well.

They are also vital in determining when the plunger was traveling through fluid. The difference in time of each change point detected by the PELT algorithm is used to calculate the time the plunger passes each collar; the plunger starts traveling through fluid and also the point at which the plunger comes to rest. Multiple levels of sound are present in the tubing acoustic data.

As the plunger travels past each collar, there are periods where there is silence, periods when it makes a sound when it passes a collar, periods when there are echoes and additional levels of sound from which we cannot draw a conclusion. The clustering algorithm identifies these items and groups them in their respective cluster. We are able to use these individual clusters to predict when a new data point in the tubing acoustic is a collar or not.

Additional analysis has to be conducted with samples from different wells, different times during the day, and data from different seasons to evaluate the impact they will have on our models and prediction.

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