STUDY OF CASING FAILURE IN UNCONVENTIONAL WELLS USING DATA ANALYSIS

A Thesis

by

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ABSTRACT

Over the last decade, there have been major changes in casing design requirements in the oil and gas industry. The changes were necessary to withstand the loads and stresses from the unconventional reservoir. However, there had been numerous reports of casing failure, indicating that the current casing design for the unconventional wells might not be adequate, resulting in a higher-than-expected failure rate in the production strings. Many factors are considered in casing design, as it goes through different stages of well completion and production. For this reason, it is difficult to address the cause of the failure. This study is carried out using statistical analysis methods to identify the most influential factors leading to the casing failure, and recommend what can be done to improve casing design by using the data analysis method.

This study focuses on a dataset from the Granite Wash play located in Texas and Oklahoma. Statistical analysis methods, including basic descriptive analysis method and logistic regression method, are employed to analyze the correlation between the failed wells and the possible factors contributing to the failure. The data analysis shows four main factors: casing size, average water used per fracture stage, average proppant used per fracture stage and casing weight, which are correlated to the casing failure in this study region.

The study concludes that data analysis can be employed in making an improvement in casing design for the wells that experience higher than usual rate of casing failure. By

following the recommendations on using data analysis, the causes of the casing failures can be found which can be used for the casing design improvements.

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Contributors

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NOMENCLATURE

α_T	= Coefficient of linear thermal expansion
API	= American Petroleum Institutes
bbl	= Barrel, 42 gallon equivalent
β_n	= Coefficient of the variable
β_o	= Y-intercept
ΔT	= Change in temperature from initial state to the final state
E	= Young's elastic modulus
ε	= Uniaxial strain
ISO	= International Organization for Standards
lbs	= Pounds
lbs/ft	= Pounds per feet
MD	= Measured depth
PSI	= Pounds per square Inch
RRC	= Railroad Commission
σ	= Uniaxial stress
σ_0	= Initial stress
x_n	= Predictor variable
TVD	= True vertical depth
Y	= Probability of outcome

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1. INTRODUCTION

A good casing design not only protects surrounding environments, but also enables trouble-free production of hydrocarbons from the reservoir rocks to the surface of the earth during the life of a well, with a proper maintenance (King 2012). Thus, it is important to have a proper design that suits different objectives of the oil and gas company at the early stage of a hydrocarbon development. The casing design process includes identifying the anticipated loads the casing string would go through during a well's lifetime, and choosing an appropriate design that can withstand the loads in the most economical way (Byrom 2015).

Due to the aggressive horizontal drilling, production practices utilizing hydraulic fracturing, some wells encounter issues with casing failures. It is also stated that the loads from the hydraulic fracturing and high dogleg severity can lead to casing connection failure and that the dogleg severity should be reduced below 8 degrees per 100 feet (Haghshenas, Hess, and Cuthbert 2017). According to Qian et al. (2015), the stress from the hydraulic fracturing would cause the formation to shear, leading to casing deformation. The propagation on the fractures created from the hydraulic fracturing operation would also cause the deformation of adjacent wells.

A casing design involves many variables such as setting depth, casing weight, casing size, casing grades and casing connections. The success of the casing design depends not only on the casing material itself, but also on other factors such as drilling, cementing and production enhancement operations such as hydraulic fracturing and acid treatment. In addition, there is always uncertainty with the casing design, as the prediction of loads and the behavior of the casing materials with multiple load cycles are not fully recognized. Thus, a design factor to accommodate this uncertainty is used for the casing design (Byrom 2015).

The casing design is an iterative process that follows at least five steps. First, the pressure loads are determined from pressure versus depth graph from the formation of interest. Second, preliminary casing size, grade and weight are chosen for different depths. Third, both dynamic and static loads for casing burst, collapse, and tension that the casing would undergo are determined, and the chosen casing is checked to see whether it can handle the loads. Fourth, adjustments are made in casing properties and the depth chosen from the second step. Lastly, the loads against the chosen casing are determined and checked (Byrom 2015).

The data set used for this paper comes from an operator called Company A, with its wells in the Granite Wash play in Texas and Oklahoma, as shown in the **Figure 1**. The study area spreads across the seven counties with three major formations targeted, the Cleveland Sandstone, Granite Wash, and Marmaton. The drilling and completion program involved horizontal drilling with multistage hydraulic fracturing operation. The casing failure rate indicates that the current casing design is not adequate to reliably withstand the loads being imposed on the casing tubulars.

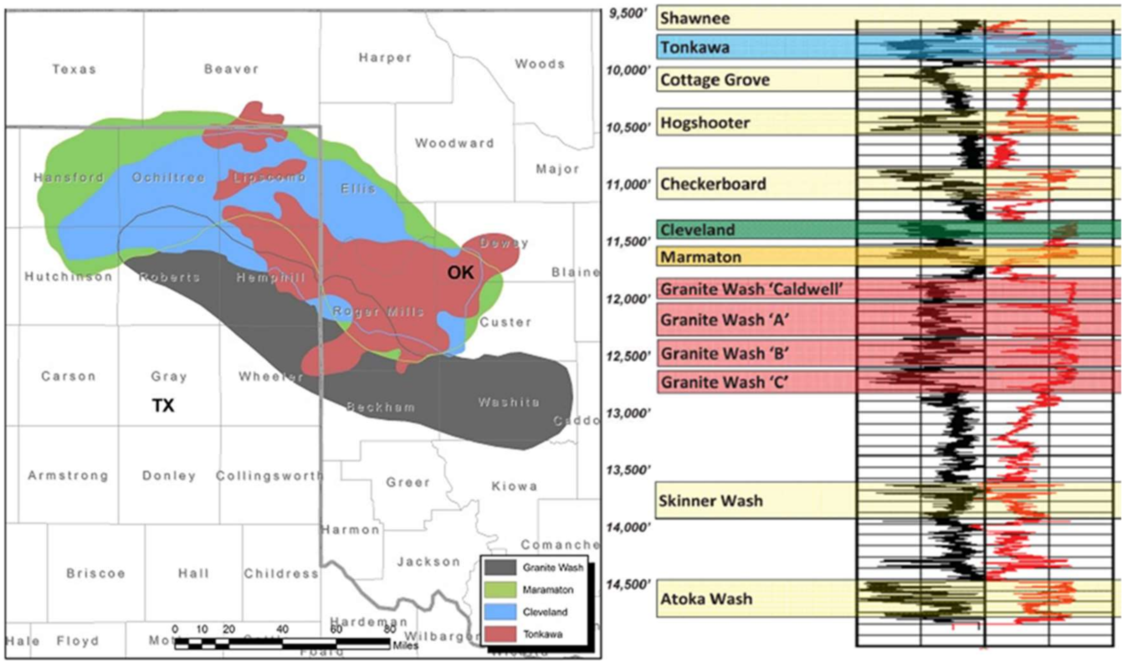

Figure 1 - Aerial map and the stratigraphic section showing the research area, Reprinted from ShaleExperts (2017).

For the above reasons, the author believes that making an improvement in the casing design in unconventional wells involving horizontal drilling and hydraulic fracturing requires a study on finding correlations between the casing failures and the variables that go into the casing design. Data analysis methods are employed in this study to find the link in variables leading to the casing failure.

2. METHODOLOGY

2.1 Data Collection

The data used can be divided into two parts: the wells with noted casing failures and offset wells with no integrity issues. The failure data, which contains 20 wells with casing issues, is provided by Company A. The data includes important information on the drilling, hydraulic fracturing and completion, which are related to the casing design.

The offset well data consists of 60 horizontal wells within the same region. Three neighboring wells for each of the failed well are selected for the data analysis. The casing design varies greatly, depending on the formation it is targeting and it is necessary to make comparison to wells within as close a proximity as possible. Offset wells drilled within 5 years of the failed wells are chosen to ensure that similar drilling and completion technologies are being compared. The data for the offset wells is from a variety of public sources. Four public domains including Railroad commission of Texas (RRC), FracFocus.org, Oklahoma Corporation Commission Oil and Gas Conservation Division, and Drillinginfo are utilized for the data collection.

Much of the data for this research is taken from the forms that are available to the public through Railroad Commission (RRC) of Texas. They include forms such as W-2 (Oil Well Potential Test, Completion or Recompletion Report), L-1 (Electric Log Status Report), P-4 (Producer's Transportation Authority and Certificate of Compliance), W-15 (Cementing Report), and Directional Survey (RailRaodCommission 2017).

The second data source is FracFocus.org, which is an online database with hydraulic fracturing information. It is maintained by the Ground Water Protection Council, and collects information related to hydraulic fracturing provided voluntarily by the oil and gas companies (FracFocus 2017).

The third data source is the Oklahoma Corporation Commission Oil and Gas Conservation Division. A wide variety of data is available from this regulatory body for the wells that are completed in Oklahoma. They include forms such as Form-1000 (Application to Drill, Recomplete or Reenter), Form-1001A (Notification of Well Spud), Form-1002A (Completion Report), Form-1002C (Cementing Report), Form-1073 (Notice of Transfer of Well Operatorship), and Directional Survey (Oklahoma 2017).

The last data source is the Drillinginfo. It provides data collection and analysis services related to the gas and oil industry. Much of the data that Drillinginfo gathers are aggregated from the public sources. Since they have large collection of data on wells, this media is used to collect information on 60 offset wells (DrillingInfo 2017).

2.2 Data Processing and Statistical Analysis Method Used

The data analysis involves processing a sparsely populated data set with many possible parameters related to casing failures into understandable and meaningful information. For this study, a statistical computing program call "R-language" is used, as it is one of the most widely used platforms available for use (Curran 2010). For a successful data analysis, the following steps are followed as suggested by Kabacoff (2015) and as shown in the **Figure 2**. Depending on the data analyzed, there are two more steps that could be taken in the data analysis, such as testing the model fit with new data set or cross-validating the model (Kabacoff 2015). Both steps are not used as the sample size is small, and partitioning the dataset for training and testing is not done for this study.

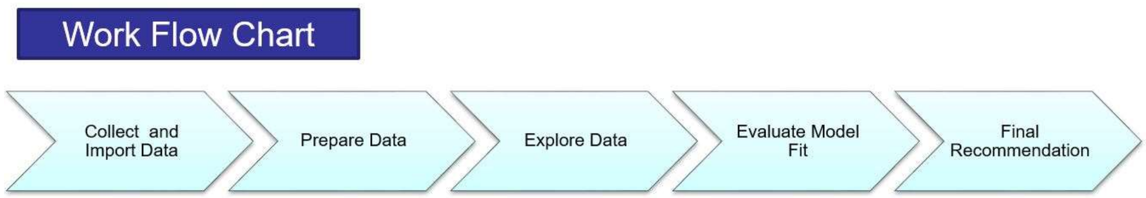

Figure 2 - Data processing steps for this study, Adapted from Kabacoff (2015).

The first step in data processing is to collect and import the data. This step consists of downloading the files, forms, and relevant information regarding the casing failure, for the analysis. The relevance of the data to the drilling and completion is determined based on 4 activities; drilling the open hole interval, casing installation, cementing installed casing and completions operations, typically hydraulic fracturing. In this analysis, data on 79 variables are collected.

The second step in the study involves preparing, and cleaning the dataset. Without a proper preparation to fit the data format to the R-language program, the data cannot be used for statistical analysis. Cleaning the dataset involves visual inspection of data and getting rid of obvious mistyped data points.

The third step involves exploring and fitting a statistical model with the data set. The data is explored using descriptive statistics, to find which variables would be good candidates to be included in the statistical analysis method. For the descriptive statistics method, the data are sorted into two distinctive classifications; qualitative (categorical) and quantitative (numerical) variables. The qualitative variables include variables such as the operator or the fracture operation season, which cannot be counted numerically. The quantitative variables include the surface temperature, or total proppant used, which can be counted numerically. Depending on the classification, different descriptive statistical methods are used. For the qualitative variables, bar plot is utilized for every variable, to see the differences between the failed and offset wells. A bar plot as shown in the **Figure 3** is used for all the quantitative variables for comparison, as well as numerical descriptive analysis such as the central tendency, dispersion, and skewness. The bar plot was useful in comparing the distribution and the central tendency of the failed and the offset data as it shows the mean, outliers, first and the third quartiles.

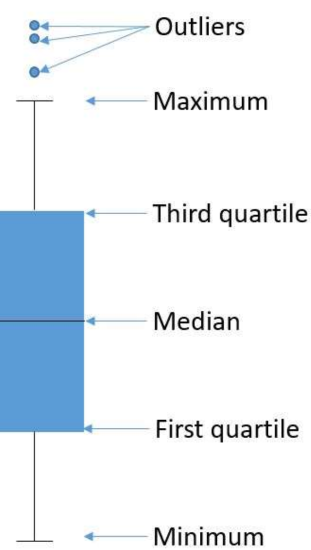

Figure 3 - Bar plot is used to compare median, and dispersion of the quantitative variables between the failed and offset wells, Adapted from Howell (2016).

The next step in the data processing flow chart involves utilizing the logistic regression method. This statistical method is suitable for predicting the binary outcomes that are not normally distributed such as failed/passed, and yes/no with multiple predictor variables (Kabacoff 2015), and in this study, casing failed or not failed. The detailed explanation on the logistic regression with regard to the assumptions, theory, and interpretation is available in Hosmer Jr, Lemeshow, and Sturdivant (2013).

In summary, the logistic regression method uses both quantitative and qualitative variables, to find an underlying relationship to the binominal response outcome. The following Eq. 1 shows the general relation of the predictor variables and the outcome (Hosmer Jr, Lemeshow, and Sturdivant 2013). The equation is in exponential function, which can produce the probability outcome between zero and one in s-shaped curve. The outcome is denoted as Y, and the predictor variables are denoted as x_n. The coefficient of the predictor variable is denoted as β_n, and the y-intercept is denoted as β_0.

$$\boldsymbol{P(Y = 1|x) = \frac{e^{\beta_0+\beta_n x_n}}{1+e^{\beta_0+\beta_n x_n}}} \quad \text{..} \quad (1)$$

The logistic regression method involves many iterations to evaluate which predictive variables contribute to the predictor variable, failure probability in this study. This means that an optimized model fit is found with the smallest number of predictor variables. Ultimately, this will lead to finding the relevant predictor variables out of the 79 that affect the casing failure in this study.

The logistic regression models are compared based on the quality of fit to see the relative accuracy of the model in predicting the failure probability (Hosmer Jr, Lemeshow, and Sturdivant 2013). The Akaike Information Criterion (AIC) is a method commonly used for the models having different number of variables used to fit the model. In this study, this method is suitable as each model have different number of predictor variables.

Missing data can be a problem in statistical analysis (Curran 2010). In this study, single imputation method, mean substitution, is used to deal with the missing data points. Without the imputation, the rows of data points related to the missing variable are deleted entirely from the analysis, leading to only a handful of data sets. Other imputation methods are not considered in this study.

The statistical methods involve many trials to evaluate and optimize the model fit. Based on the logistic regression analysis, the last step in this study is to recommend which predictor variables are relevant in predicting the casing failure, by examining the goodness of the fit, and recommend on how to initiate the change in casing design practice.

3. RESULTS AND DISCUSSIONS

3.1 Analysis Using Descriptive Statistics – Numerical Interpretation

The first data analysis result comes from the descriptive statistics method. First, the dataset is grouped into entire data, failed wells data, and offset wells data, for comparison. There are a total of 79 predictive variables for the data analysis: 59 numerical and 20 categorical variables. For the 59 numerical variables, descriptive metrics such as the mean, coefficient of variation, percentage of the missing observations, skew, and kurtosis, are found for the three groups of dataset. This analysis is done to see which predictive variables would be worth pursuing further for the analysis.

Table 1 summarizes the results from the comparison of the entire data, failed and offset wells variables. The numerical differences of means, coefficient of variation, and skew are compared between the total dataset, failed and offset wells. Out of the comparison, the 11 predictive variables from each of the three descriptive metrics that have the most differences in the value are selected. These selected variables have descriptive metrics that are at least 25% different from the failed and offset wells. Some variables have two or three descriptive metrics that differ, such as the number of centralizers, leading to 22 predictive variables being selected. The checkmark on the table indicates which descriptive metric is different for each of the variables. The selected variables are listed in ascending order in respect to the percentage of the missing data points. The missing data points of a variable do not represent the underlying trend of that variable (Little and Rubin

2014). Thus, the higher the missing data points, the weaker the relationship between the variables.

Table 1 - the comparison result of three descriptive metrics with percentage of missing observation showing 22 selected variables with the most differences from each metric.

Variable	Descriptive Metrics for the predictive variables: Mean	Coefficient of Variation	Skewness	% of missing observation
1 TVD (ft)			✓	0%
2 Size of Casing (in)		✓		0%
3 Toe TVD (ft)		✓		1%
4 Acid Pumped (Yes/No)	✓			3%
5 Heel MD (ft)	✓	✓		4%
6 Max inclination (degree)		✓	✓	5%
7 Total Proppant used (lbs)	✓	✓		5%
8 DogLeg Severity (degree)		✓	✓	6%
9 Frequency of DogLeg over 10 degrees			✓	8%
10 Location(MD) of the most severe Dogleg (ft)			✓	8%
11 Time Lapse btw drilling and fracturing (days)	✓			13%
12 Number of Fracture Stages per 1000 ft(Frac density)			✓	43%
13 Average Water used per stage	✓			43%
14 Ave proppant used Per stage (lbs)	✓	✓		43%
15 Casing Weight (lbs/ft)	✓	✓		44%
16 Cement Volume (cu. ft)	✓	✓		50%
17 Cement Height (ft)	✓		✓	53%
18 Top of the cement (fT)			✓	55%
19 Max frac Pressure (psi)			✓	61%
20 Acid Volume (bbl)	✓			76%
21 Hours waiting on cement before drill out (hr)		✓	✓	90%
22 Number of centralizer	✓	✓	✓	91%

The results from the numerical interpretation are valuable in distinguishing which variables are worth the effort of pursuing in the next stage of the data analysis, using the logistic regression method. Using all the 79 variables does not help in making inference on the casing failures if they only have a weak correlation; thus, only 22 predictive variables are pursued for further analysis.

3.2 Analysis Using Descriptive Statistics – Visual Interpretation

The visualization of the data is more suitable in many cases than tables and text **(**Kabacoff 2015**)**. Also, out of all the predictive variables there are twenty categorical variables which cannot be explained with the numerical descriptive metrics. Thus, box plots and bar plots are used for the variable comparisons of qualitative and quantitative variables between the failed and offset wells. Although 52 plots were visually analyzed, only four comparisons that the author thinks important are shown in this comparison. The visual analysis is subjective in nature, and is used with the numerical analysis above to draw conclusion. The explanation on the box plot can be found in the methodology section.

The two predictive variables related to the tortuosity of the well, which can affect the integrity of the casing adversely (Bang et al. 2016) show mixed results from the visual analysis, which is contrary to what one would typically believe. **Figure 4** shows the box plot of the maximum inclination between the failed and offset wells. It indicates that the failed wells have the tendency of higher maximum inclination, compared to the offset wells. It should be also noted that the dispersion of the data is much smaller for the failed wells and that the higher inclination could be indicative of the failed wells being more toe-up than the offset wells.

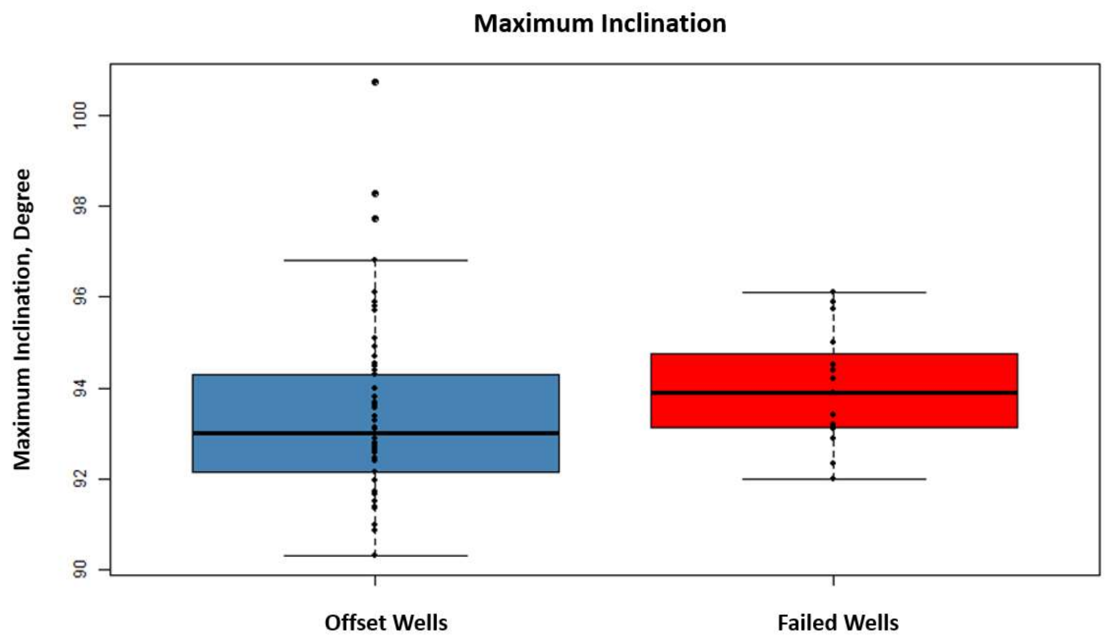

Figure 4 - Box plot comparison of the maximum inclination between the failed and offset wells showing the median maximum inclination of the failed wells being higher.

The **Figure 5** shows the maximum dogleg severity comparison, indicating that the failed wells have a median that is lower than the offset wells. This finding is contradictory to the relationship between the casing failure and the tortuosity of a well (Bang et al. 2016). One important distinction is the two outliers on the failed wells. These two wells had the maximum dogleg severity of over 20° per 100 ft. Overall, it shows that the maximum dogleg severity has negative correlation with casing failure with failed wells having lower dogleg severity.

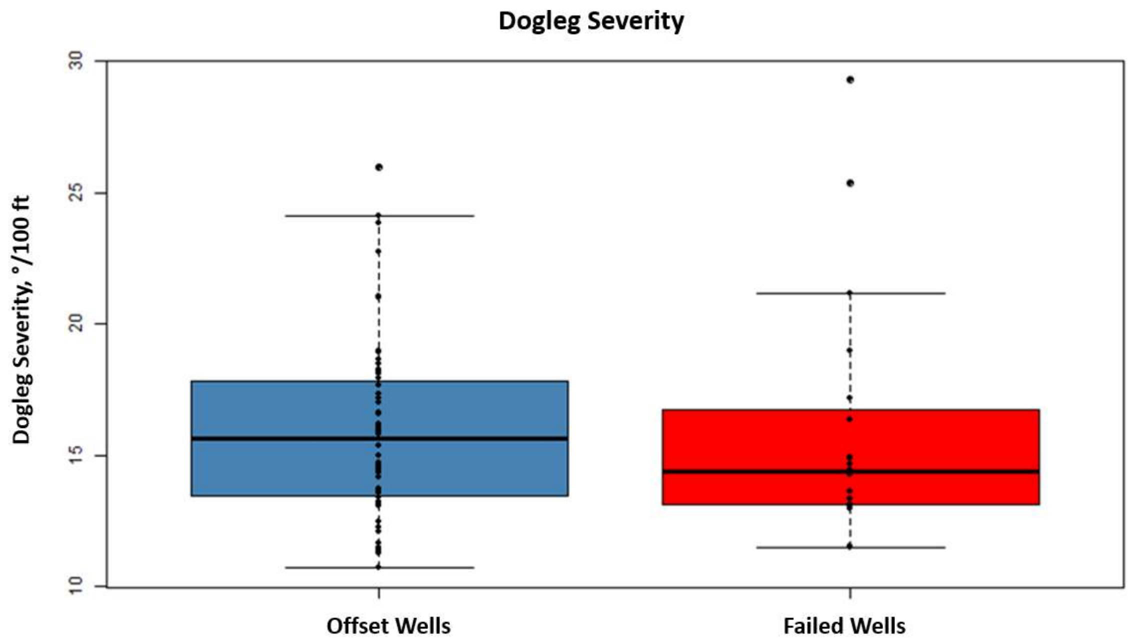

Figure 5 - Box plot comparison of the most severe dogleg between the failed and offset wells showing the median of the failed well.

Figure 6 shows the bar plot of the month of the fracture operation for both failed and offset wells. The result indicates increased failure rate between January and June. Although this is associated with lower temperature overall, there is an increase in failure rate in June, when the surface temperature is higher relative to the rest of the months. This visual plot indicates that there is a definite relation of the failed well to the predictive variable.

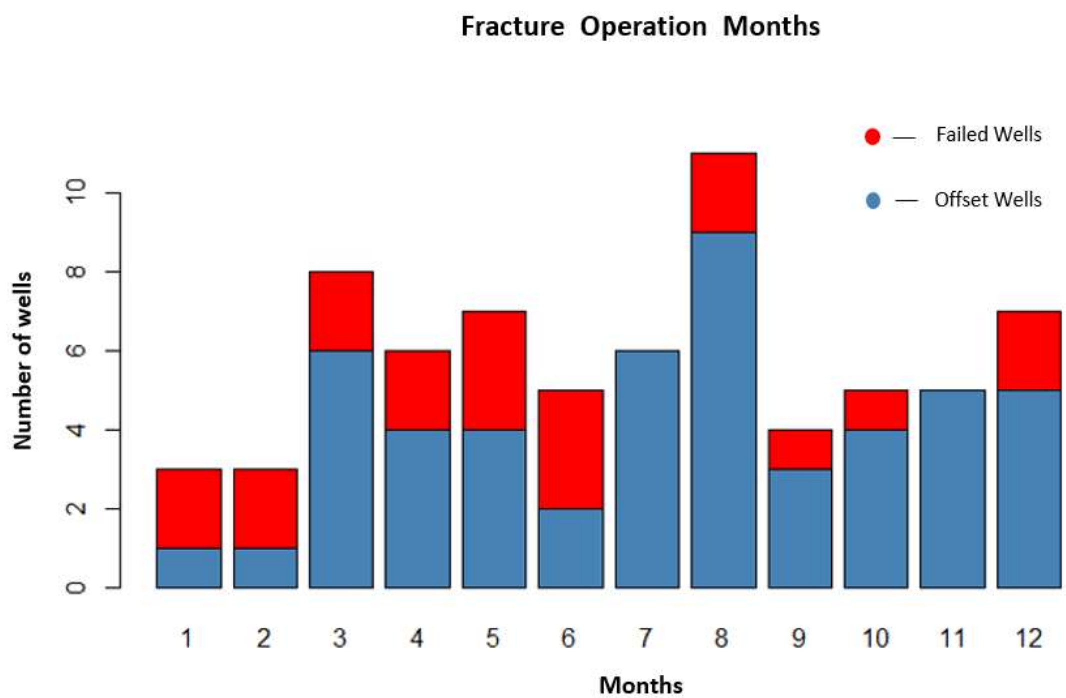

Figure 6 - Bar plot of the hydraulic fracture operation month between failed and offset wells indicates more wells failed that are fractured during the colder months except June.

Figure 7 shows the bar plot of the hydraulic fracture operation month between failed and offset wells that are drilled by Company A. There are a total of 466 horizontal wells drilled by Company A in the region between 2011 and 2014. The mean failure rate is 4.3 percent. It shows that January and February had the highest failure rate followed by May. Generally, failure rates are higher than the mean during the beginning of the year. This visual descriptive analysis represents the temperature effect on the failure rates better than the previous comparison, since the wells completed by Company A have more similar design characteristics, compared to just offset wells within the region. Thus, we can see the temperature effect on the failure rate better with this bar plot.

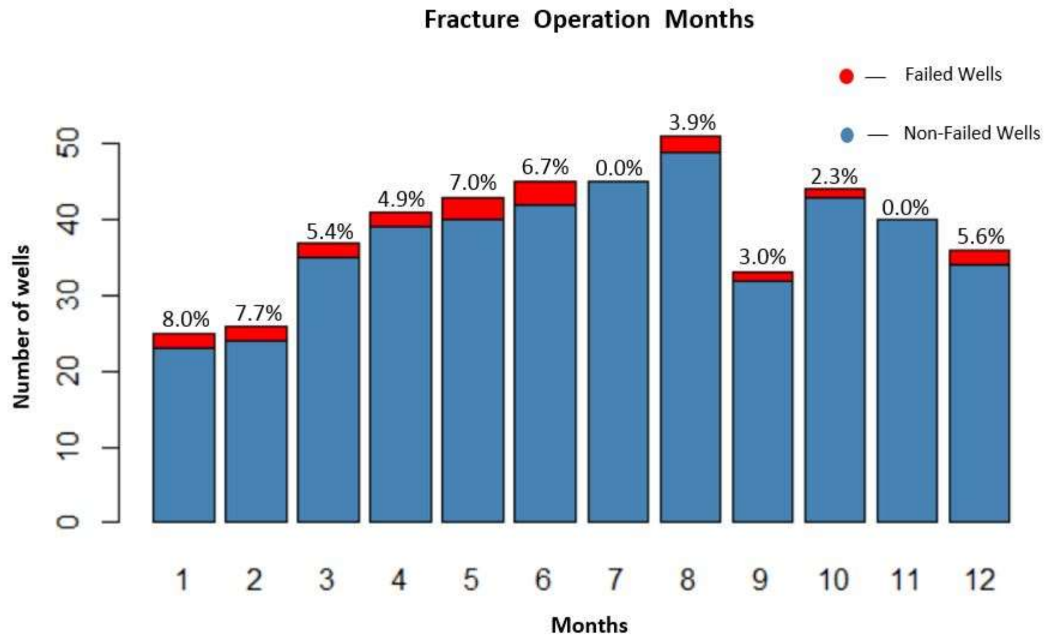

Figure 7 - Bar plot of the hydraulic fracture operation month of all the wells drilled by Company A indicates more wells failed that are fractured during the colder months except June.

Other noticeable predictor variables from the visual analysis include the following:

- Time lapse between spud date and the first day of drilling – the box plot indicates that the failed wells had more days during this period.
- Maximum fracture operation pressure – the box plot indicates that the failed wells had higher maximum operating pressure, while performing the hydraulic fracturing operation.
- Mean temperature on the day of fracturing – the box plot indicates that the failed wells had a slightly lower mean temperature. This result supports the claims from some literature on the increase in the temperature difference during the hydraulic

fracturing job leading to casing failure due to thermal shock (Wu, Knauss, and Kritzler 2008).

- Total lateral length – the box plot indicates the failed wells had longer lateral length. This indicates that the failed wells were drilled more aggressively to cover the longer lateral section (Liston et al. 2014), which can affect the overall casing integrity.

3.3 Analysis Using Logistic Regression Methods – Without Imputation

The dataset contains many missing values. If the imputation method is used to fill the missing value, it would create some form of bias in the analysis (Kabacoff 2015). Thus, the first logistic regression method, model one, uses 22 predictive variables from the numerical interpretation to see if any of these 22 predictive variables would have any correlation to the casing failure, without any imputation method. It is preferred to have a dataset without any missing data points, because the logistic regression uses only a complete data set for the analysis. For example, if an offset well is missing one variable such as a maximum fracture pressure, the logistic regression omits that offset well as a whole. This leads to potentially having limited data, making the logistic regression analysis less accurate. As per the author's subjective discretion, predictive variables with more than 40% of the data points missing are excluded for further analysis in this section, which led to only 10 predictive variables being used for the second model regression method without any imputation. This data set is not free from missing data; six wells out of 80 wells are left out from the analysis, due to the missing data. Although the missing data is not a major issue in this case as less than 10% of data is missing, the logistic regression result did not display any meaningful result, as shown in **Table 2**. The analysis shows that these 10 predictive variables together would not give any meaningful predictive model, as can be seen from the last column, p-value. The p-value is a result from testing a model assuming that the estimated coefficient is zero. Generally, lower the p-value, more significant the variable is to the model (Hosmer Jr, Lemeshow, and Sturdivant 2013). The variables that have higher than 0.05 for the p-value are usually ignored when fitting a regression model.

Table 2 - Logistic Regression fit of second model with 10 predictive variables without any imputation showing no statistical significance.

Predictive Variables	Coefficients of Estimate	P-Value
(Intercept)	-19.7	0.237
TVD	0.0007137	0.812
Toe.TVD	-0.002163	0.433
Acid.Pumped..yes.No.	0.7251	0.416
Heel.MD	0.001388	0.299
Max.inclination	0.1986	0.281
Total.Proppant.used	-6.687E-07	0.261
DogLeg_Severity	0.0845	0.404
Frequency.of.DogLeg.over.10.degrees	-0.1222	0.14
Location.MD..of.the.most.severe.Dogleg	0.00003491	0.918
Time.lapse.btw.drilling.and.fracturing	0.0097	0.275

Predictive variables related to the tortuosity of the well have been found to have some correlation to the casing failure from the visual interpretation. The descriptive statistics are very subjective, and the more advanced methods such as logistic regression analysis, which is more objective, would test the variables to see if they have any significant relations to the casing failure. The third model uses these variables to see if any significant variables that lead to the failure could be found. The result from **Table 3** shows that having all four predictive variables related to the tortuosity does not produce any meaningful result.

Table 3 - Logistic Regression Fit of four predictive variables from the descriptive analysis related to tortuosity without any imputation showing no statistical significance.

Predictive Variables	Coefficients of Estimate	P-Value
(Intercept)	-2.14E+01	0.13
Max.inclination	2.34E-01	0.132
DogLeg_Severity	1.28E-02	0.874
Frequency.of.DogLeg.over.10.degrees	-4.65E-02	0.511
Cum.DLS.in.lateral.section & build.section	-2.02E-03	0.389

Since a meaningful result could not be found from using all the variables related to tortuosity, individual variables are tested by themselves to see if any predictive variables without imputation method would yield any statistical significance. The result shows that none of the predictive variables related to the tortuosity alone would produce a model fit. Lastly, the time lapse between drilling and hydraulic fracturing activity and the mean temperature on the day of fracturing are separately tested as a predictive variable to see if these variables would provide a model fit. The result did not produce any significant indication for predicting the casing failure without the imputation. This analysis approach indicates the following:

- The descriptive statistics alone do not give an objective conclusion to predicting which variables affect failure, confirmed from the logistic regression analysis.

- Logistic regression analysis using dataset without imputation does not provide any correlation between predictive variables and the casing failure in this study area.

3.4 Analysis Using Logistic Regression Methods – With Imputation

The 16 predictive variables that have more than 50% of the data points instead of 40% are chosen from the 22 predictive variables found from the descriptive analysis for the logistic regression analysis with imputation methods. The reason that more variables are chosen is that these variables are going to go through the imputation method unlike the previous analysis. The variables that are missing more than 50% of data points are excluded; otherwise the single imputation method using mean value would not work (Kabacoff 2015). The result is shown in **Table 4** and shows casing size, average water used per fracture stage, average proppant used per fracture stage, and casing weight having statistical significance as the last column indicates.

Table 4 - Logistic Regression Fit of 16 variables from the descriptive analysis metrics with single value mean imputation showing statistical significance.

Predictive Variables	Coefficients of Estimate	P-Value
(Intercept)	-6.67E+01	0.188405
TVD	6.09E-03	0.100633
Size.of.Casing	1.49E+01	0.008898
Toe.TVD	-3.17E-03	0.217131
Acid.Pumped..yes.No.	1.53E+00	0.286908
Heel.MD	-3.03E-03	0.218898
Max.inclination	2.37E-01	0.58509
Total.Proppant.used	-2.65E-07	0.817268
DogLeg_Severity	1.95E-01	0.240851
Frequency.of.DogLeg.over.10.degrees	-2.87E-01	0.082684
Location.MD..of.the.most.severe.Dogleg	-1.29E-04	0.752925
Time.lapse.btw.drilling.and.fracturing	1.03E-02	0.30799
Number.of.Fracture.Stages.per.1000.ft.Frac.density.	2.24E-01	0.290185
Average.Water.used.per.stage	2.86E-05	0.011453
Ave.proppant.used.Per.stage	-4.10E-05	0.067935
Casing.Weight.for.this.casing	-1.82E+00	0.000543
Cement.Volume..cu..Ft.	1.04E-03	0.484099

Since the other 11 predictive variables do not have meaningful statistical significance, a reduced model fit with only these four variables was created to see if it produces any difference. This process is necessary to see how much each relevant variable would affect the probability of failure, without the noises created from the variables that do not have any correlation. The result from the reduced model fit from **Table 5** shows that these four variables have significance in predicting the casing failure, as per the logistic regression analysis.

Table 5 - Logistic Regression Fit of four variables from the descriptive analysis metrics with single value mean imputation showing statistical significance.

Predictive Variables	Coefficients of Estimate	P-Value
(Intercept)	-2.30E+01	0.006381
Size.of.Casing	8.98E+00	0.000326
Average.Water.used.per.stage	1.85E-05	0.005232
Ave.proppant.used.Per.stage	-2.26E-05	0.0435
Casing.Weight.for.this.casing	-1.39E+00	0.000124

An attempt is made to see if the analysis of the third model, which utilized the variables from the visual interpretation, would be any different if the imputation method is used. The sixth model result comes from using four variables with the imputation that are related to the wellbore tortuosity. The frequency of the dogleg over 10°, cumulative dogleg in lateral and build section, dogleg severity and max inclination, did not indicate any statistical significance in predicting the casing failure, even with the imputation method, as shown in the **Table 6.**

Table 6 - Logistic Regression Fit of four variables related to tortuosity with single value mean imputation showing no statistical significance.

Predictive Variables	Coefficients of Estimate	P-Value
(Intercept)	-2.24E+01	0.112
Cum.DLS.in.lateral.section.plus.build.section	-2.01E-03	0.391
Frequency.of.DogLeg.over.10.degrees	-4.35E-02	0.54
DogLeg_Severity	1.14E-03	0.989
Max.inclination	2.46E-01	0.112

The other predictive variables, model number seven, from the visual descriptive analysis – time lapse between drilling and fracking, mean temperature on the day of the fracturing operation, maximum fracture operating pressure, lateral length, and fracture operation month – result in fracture operation month being slightly relevant to the prediction of the casing failure as shown in **Table 7**. It should be also noted that the coefficients of estimate are negative for the fracture started month, indicating that the casing failure rate decreases with increase in temperature: the later the year, lower the temperature, the less the failure rate.

Table 7 - Logistic Regression Fit of five variables from the visual descriptive method with single value mean imputation showing no significant statistical significance.

Predictive Variables	Coefficients of Estimate	P-Value
(Intercept)	-3.90E+00	0.2206
Time.lapse.btw.drilling.and.fracturing	2.29E-03	0.6836
Mean.Temperature.F.on.the.day.of.Fracturing	-1.52E-02	0.3155
Max.frac.Pressure	3.00E-04	0.2022
Lateral.Length	4.56E-04	0.2656
frac.start.month	-1.49E-01	0.0992

The regression analysis is done with all the predictive variables that have statistical significance from the previous analysis. **Table 8** shows that except the fracture start month, other four variables would be useful in predicting the casing failure. The analysis indicates that casing weight has negative correlation to the casing failure. This means the wells with heavier casing weight tend to fail more, compared to the wells using the lighter weight casing. It should be also noted that fracture start month does not have a strong correlation with the casing failure to be included.

Table 8 - Logistic Regression Fit of 5 predictive variables that have statistical significance shows fracture operation start month does not have statistical significance when combined with other variables.

Predictive Variables	Coefficients of Estimate	P-Value
(Intercept)	-2.18E+01	0.014378
Size.of.Casing	8.73E+00	0.000794
Average.Water.used.per.stage	1.82E-05	0.005823
Ave.proppant.used.Per.stage	-2.15E-05	0.048985
Casing.Weight.for.this.casing	-1.35E+00	0.00038
frac.start.month	-1.38E-01	0.234706

The visual descriptive analysis with the maximum pressure indicates that the failed wells used higher pressure than the offset wells. The increase in pressure due to the hydraulic fracturing operation affect the burst load the casing would go through. The increase in the burst load does not directly lead to the casing failure. If the casing wall thickness is greater to withstand the load, the casing would not have any issue with higher fracture operation pressure. Thus, logistic regression analysis is carried out to see whether the correlation between the maximum pressure and the casing wall thickness would have any relation to the casing failure. It shows from **Table 9** that the statistical significance is low to consider any relation of the new variable, fracture pressure over wall thickness, to the casing failure probability in this field.

Table 9 - Logistic Regression Fit of maximum pressure over casing wall thickness shows no statistical significance to the casing failure.

Predictive Variables	Coefficients of Estimate	P-Value
(Intercept)	-2.69E+00	2.67E-01
Frac.Pressure.Wallthickness	5.54E-05	0.46

In this section, a total of five models which employed the logistic regression method with data imputation are analyzed. As per the logistic regression analysis with imputation, it showed some of the variables which seemed to indicate a correlation to failure in the descriptive statistics not contributing to the casing failure. This confirms the previous statement that the descriptive statistical analysis is used to summarize the dataset, not to infer a conclusion, as it is a very subjective method in analyzing the data. The second finding is that the data imputation is necessary for a logistic regression method to work when the dataset contains many missing data points. Finally, we found that the size of casing, average water used per fracture stage, average proppant used per fracture stage, and casing weight for the casing are the only predictive variables that seem to have a significant impact on the failure of casing strings and thus should be considered when making an improvement in the casing design in this field, with minor significance in the fracture operation month.

3.5 Discussion on Physics-based Reasons for Statistical Results

The analysis leads to a total of seven factors that correlates with casing failure. They are size of casing, average water used per fracture stage, average proppant used per fracture stage, casing weight, maximum pressure used in hydraulic fracturing operation, temperature difference the casing goes through, and lateral length covered by the well. Looking at how each of the variables affect the casing design allows the author to see how these variables relate to casing design.

The standards for the oilfield casing properties are developed by the American Petroleum Institutes (API), and they are now being advanced by the International Organization for Standardization (ISO) (Byrom 2015). Per standards, the property of the casing depends on the combined parameters of casing size, casing grade and weight. The analysis indicates a positive correlation between the increased size of the casing and the increased failure probability**.** The strength of the casing goes down with increasing casing size assuming other parameters are fixed. The positive correlation between the casing size and the failure rate shows that decrease in the casing strength due to utilization of bigger casing size led to increase in probability of casing failure. The casing size is usually determined by the required hydraulic fracturing job, and the production rate (King 2012). Accordingly, the casing weight and/or the casing grade should be changed to accommodate the decrease in the casing strength due to the increase in casing size to decrease the casing failure rate.

For the casing weight, the negative correlation between the size of the casing and the failure probability indicates that failure will decrease with the increase in the casing weight. As the casing weight increases, the strength of the tubing increases. In other words, the casing with the heavier weight can withstand higher loads exerted on the casing (Byrom 2015) leading to less casing failures.

The temperature fluctuation on the casing can lead to thermal shock which can decrease the strength of the casing. During the lifetime of the well, the casing must go through several instances of temperature change. In this analysis, hydraulic fracturing operations lead to several thermal cycles. Unsurprisingly, there is a correlation between the casing failure and the month of the hydraulic fracturing operation. The visual descriptive analysis indicates more wells fail when the surface temperature is colder; the casing must go through a larger temperature difference assuming the bottom hole temperature is constant. The one-dimensional Hook's law showing axial stress change due to the temperature change is shown:

$$\sigma = \sigma_0 + E\varepsilon - E\alpha_T \Delta T \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.... \quad (2)$$

Eq. 2 indicates that the change of temperature can affect the casing strength by changing the stress state. If the casing is not fixed, the casing will expand and shrink due to the thermal effect, and the casing will only experience strain. However, if the casing is fixed, it only undergoes stress. In this case, the casing will go through a greater buckling since the temperature change is greater (Byrom 2015).

The visual descriptive analysis shows there is a positive correlation between the increase in lateral length and the increase in failure rate. As Sanchez, Brown, and Adams (2012) pointed out, the increase in lateral length without proper centralizer placement can lead to the following: 1) higher loads on the casing due to the drag and higher torque, 2) more buckling (sinusoidal and helical), 3) more well cleaning issues leading to higher friction, 4) more enlarged, 5) an increase in hydraulic-related issues due to annular clearance. Clearly, there is a positive correlation between the failure rate and the increased lateral length.

The factors related to hydraulic fracturing, average water used per fracture stages, average proppant used per fracture stages, and the maximum pressure are shown to have correlation with the casing failure in this study area. These factors all contributes to the load change that the casing experiences. The hydraulic pressure is mainly a function of the composition of the fluids being pumped and the flow rate of the fluid being pumped (Daneshy 2011). As the pressure increases, the casing goes through higher burst load. This explains why there is a positive correlation between the increase in average water used per fracture stage and the increase in casing failure rate. This also explains why high pressure being is correlated to the casing failure. Unexpectedly, there is negative correlation between the average proppant used per fracture stage and the casing failure which may be due to the company A intentionally using less proppant to achieve higher fracture pressure, or due to concerns about pressure increase from the proppant screen-out occurrence which can dramatically increase the burst load (Byrom 2015).

3.6 Recommendations for the Casing Design Improvement

The ultimate goal of this effort is not to simply generate a list of potential risk factors for casing failure. The value in an analysis such as this is the resulting change in practices that leads to a reduction in the rate of future casing failures. While this analysis represents an early stage of a larger effort, there are applicable findings for a practicing engineer to consider when designing production casing for horizontal, hydraulically fractured wells. At this point, there would appear to be five main variables which must be addressed to improve reliability in unconventional well production casing design:

- Size of the casing – from the regression analysis, it is found that the size of the casing had positive correlation to the casing failure probability, which means that the wells that using bigger casing size are more likely to fail, compared to the offset wells.

- Average water used per fracture stage – it is found that the amount of water used per hydraulic fracturing had a positive correlation to the casing failure probability. This means that wells that used more water for their hydraulic fracturing operation had higher chance of casing failures.
- Average proppant used per fracture stage – it is found that the amount of proppant used as per hydraulic fracturing had negative correlation to the casing failure probability, which means that wells that used less proppant had a higher chance of casing failure.
- Casing weight – it is found that the casing weight had a negative correlation to the casing failure probability: thus, the lower the casing weight, the higher the chance of casing failure.
- Fracture start month – it is found that the fracture start month had a negative correlation the casing failure probability. This means that when the hydraulic fracturing operation is carried out in the beginning of the year, when the weather is colder, the probability of casing failure increases.

4. CONCLUSIONS

This study examines a data analysis method in making casing design improvement. The results from the data analysis show the following conclusions:

- The descriptive statistical method alone cannot be used to come to a conclusion in the casing failure analysis. It should be used with other data statistical methods, such as regression analysis, to arrive at a conclusion on the relation between the predictor variable and the response variable.
- There are four variables: size of the casing, average water used per fracture stage, average proppant used per fracture stage, and casing weight, having correlation to the casing failure of the wells in this region.
- The data analysis itself does not make a direct suggestion in the casing decision. It only pinpoints the variables that have correlation to the casing failure. The operator needs to make the design changes based on the variables that are pointed as having relation to the casing failures.
- The factors affecting the tortuosity do not appear to contribute to the casing failure.
- Increase in the total days spent between the spud data and the beginning of the hydraulic fracturing operation indicates a possible increase in casing failure rate.
- Although the data is limited, the maximum hydraulic fracture treatment pressure has a positive correlation with the casing failure.

- The temperature on the day of hydraulic fracturing has a negative correlation with the casing failure, meaning a slightly higher risk of failure on days with lower temperatures.
- The lateral length of the wellbore has a positive correlation with the casing failure, meaning that longer laterals could have an increased risk of failure.

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