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Cleanliness Correlation of Mono Ethylene Glycol (MEG) as Thermodynamic Hydrate Inhibitor to forecast Fresh Injection Period using Supervised Machine Learning

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Abstract. Production in the context of oil and gas can be defined as the total flow rate of hydrocarbon components with several other components such as water, CO_2, H_2S, and soil from production wells, then flows through a pipeline to the processing facilities. Oil and gas production can be limited by several factors, one of which is the issue of flow assurance such as gas hydrate, which can result in a loss of production opportunity (LPO) due to gas hydrate blockage. The most common hydrate formation prevention method is injecting hydrocarbon fluid with antifreeze chemicals called thermodynamic inhibitors such as mono ethylene glycol (MEG). However, dissolved solids contained in produced water may precipitate and tend to deposit in surface facilities including the Mono Ethylene Glycol Regeneration Unit (MRU). These can plug the MEG injection system and result in potential hydrate formation. This paper deals with how actual problems of plugging due to scaling or fouling on the MEG injection system can be minimized by analyzing process parameters and laboratory analysis results using supervised machine learning. The study suggests that machine learning can be used to predict the problem occurrence by observing the cleanliness level of lean MEG that correlates with some process parameters such as hydrocarbon flow rate, CO_2 content, and wellhead flowing pressure. If the cleanliness level is above specification, the MEG injection system is assumed to be possible plugging, otherwise not plugging. Some supervised learning algorithms are compared to evaluate the performance of plugging possibility prediction. This result can be used to determine and optimize MRU operation, monitoring, and maintenance strategy.

Keyword(s): Gas Production, Gas Hydrate, Mono Ethylene Glycol, Loss of Production Opportunity.

1 Introduction

Production in the context of oil and gas can be defined as the total output from production wells in the form of mass flow of hydrocarbon components with several other components such as water, CO_2, H_2S, and soil from production wells then flows through a pipeline to the processing facilities (Elgsaeter et al, 2008). Oil and gas production can be limited by several factors, one of which is the issue of flow assurance such as gas hydrate, which can result in a loss of production opportunity (LPO).

Gas hydrate is one of five solids that commonly cause flow assurance issues besides asphaltene, paraffin wax, inorganic scale, and naphthenate (Gudmundsson, 2018). Gas hydrates are crystalline solids consisting of water and gas where gas molecules (guest) such as methane, ethane, propane, and CO_2 are trapped in a water cage called cavities (hosts) which are composed of hydrogen bonds with water molecules (Sloan and Koh, 2008). Clathrate or gas hydrate formation is not a chemical reaction but a physical process under certain conditions which are generally at high pressure and low temperature (Sloan et al, 2011). The formation of hydrate in gas systems can block fluid flow in process facilities.

As a common problem in the oil and gas industry, gas hydrate formation prevention and mitigation should be considered during the production lifetime. The most popular method is to inject hydrocarbon fluids with antifreeze chemicals called thermodynamic inhibitors such as methanol, mono-ethylene glycol, and diethylene glycol (Gudmundsson, 2018). This method is often used compared to other mitigation strategies including heating and pigging methods that contribute to Non-Productive Time (NPT). Mono ethylene glycol (MEG) is generally chosen as a hydrate inhibitor in gas pipeline transportation instead of methanol because it can be regenerated and reused to reduce operating costs (Yong and Obajinesu, 2015). However, several problems often occur in the MEG Regeneration Unit (MRU) such as loss of glycol, scaling and fouling, hydrocarbons that are carried over in the regeneration system, and leaks in the pump (Haque, 2013).

In the case of Field K in Indonesia, the problem was plugging in the MEG injection system. Consequently, the MEG injection flow stopped and might cause hydrates formation in the pipeline and production manifold. Moreover, operating conditions of hydrocarbon fluid had entered the envelope of gas hydrate formation. Thus, it is required to find the root cause and predict plugging at the MRU injection system by considering the process parameters. The proposed method is machine learning (ML), which can be used to analyze large-scale historical data during production. In addition, ML can predict automatically, in real time, and accurately so that the prevention and mitigation strategy can be determined more precisely.

Therefore, this paper aims to assist oil and gas operators to conduct a root cause, prediction, and mitigation study of plugging in MRU using ML by considering the process parameters. The expected output is the cause of plugging and the period during which plugging is most likely to occur. Hence, this result can be used to determine and optimize MRU operation, monitoring, and maintenance strategy.

2 Methodology

The imaginary field is used since the actual field data are limited and not publicly accessible. Thus, the ML approach method is emphasized in this study to predict the plugging in the MEG Regeneration Unit (MRU).

2.1 Data collection

Plugging, in the case of Field K, can be considered and determined by the cleanliness level of lean mono ethylene glycol (MEG). Cleanliness can be defined as the number of solid particles in a fluid. The company has set safe criteria for the cleanliness level in the MRU below class 8 based on SAE AS4059. If the cleanliness level exceeds the specifications, the MEG injection system can be assumed ‘possible plugging’.

The ratio of possible plugging and not plugging after applying the specification of cleanliness in the dataset can be illustrated in Figure 1.

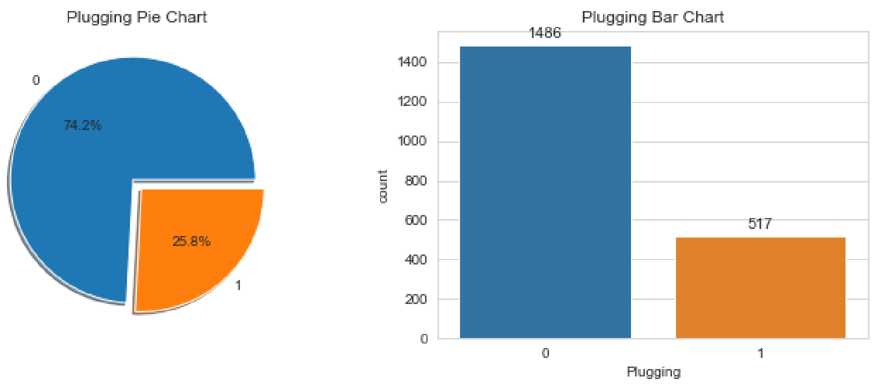

Figure 1. Comparison between Possible Plugging and Not Plugging in The Dataset

Some of the parameters considered in this study consist of gas flow rate, condensate flow rate, produced water flow rate, CO_2 content, and flowing pressure since the actual field data is not available. However, these imaginary data are sufficient to represent the cleanliness level in Field K. Produced water flow rate, for example, is most considered in this study because plugging may occur due to the amount of dissolved salt and iron that is carried to the MRU. According to the laboratory analysis report of collected scale materials samples from the fire tube and reboiler of MRU by Haque (2012), iron is the main element of scale and is sourced from produced water that comes into contact with the exchanger. In addition, scale is formed as carbonate and bicarbonate of Fe, Ca, and Mg. Therefore, by increasing produced water flow rate, there will be likely more solid contents in the hydrocarbon fluid and flow to the surface facility. Consequently, a lot of dissolved solids will be carried by produced water after going through a multi-phase separator and tend to deposit in the MRU system.

2.2 Data preprocessing

Data with possible plugging was labeled with a value of 1 in this study, otherwise 0. The dataset was subsequently divided randomly into a training set and a test set with the most common split ratio of 8:2. Thus, before splitting into a training set and test set, the dataset was shuffled to distort the ordering of the data.

2.3 Machine learning algorithms

This study aims to obtain a correlation among the parameters with the possibility of plugging by training the model through a large amount of historical data. The form of supervised learning was chosen for this study since the dependent variable (target) and independent variables (predictor) have been exactly known. Some common supervised learning algorithms, including logistic regression (LR), support vector machine (SVM), decision tree (DT), random forest (RF), artificial neural network (ANN), light gradient boosting machine or lightGBM (LGBM), extreme gradient boosting or XGBoost (XGB), naïve Bayesian classification (NBC), and K-nearest neighbor (KNN) algorithm, are compared to evaluate the performance of plugging possibility prediction.

2.4 Model performance evaluation

The accuracy of different algorithms is evaluated by two performance metrics: accuracy and F1-score. These are popular error metrics for classification models whose score ranges between 0 as the worst and 1 as the best possible score.

3 Result and discussion

3.1 Root cause analysis

The problem of Field K is the actual case in Indonesia and started when high pressure at the discharge of the lean mono ethylene glycol (MEG) injection pump triggered the alarming activation. Nevertheless, there was no lean MEG flow out of the injection line. Furthermore, the laboratory analysis results showed that the value of cleanliness was outside the criteria set by the company. Therefore, it concludes that there was plugging due to scaling or fouling in the lean MEG injection system. If this plugging continues, the injection of lean MEG as a hydrate inhibitor will stop and results in the formation of hydrates in the pipeline and production manifold after a certain time.

Moreover, the subsea wellhead is located in the deep sea with fluid operating conditions that have entered the envelope of gas hydrate formation. Although in this case, gas hydrates had not caused blockage problems in the pipeline and production manifold systems with no indication of pressure anomalies, the formation of gas hydrates still needs to be prevented and mitigated by ensuring the lean MEG flow continues to operate normally and does not exceed the duration of hydrate formation until causing a blockage if plugging occurs in the lean MEG injection system.

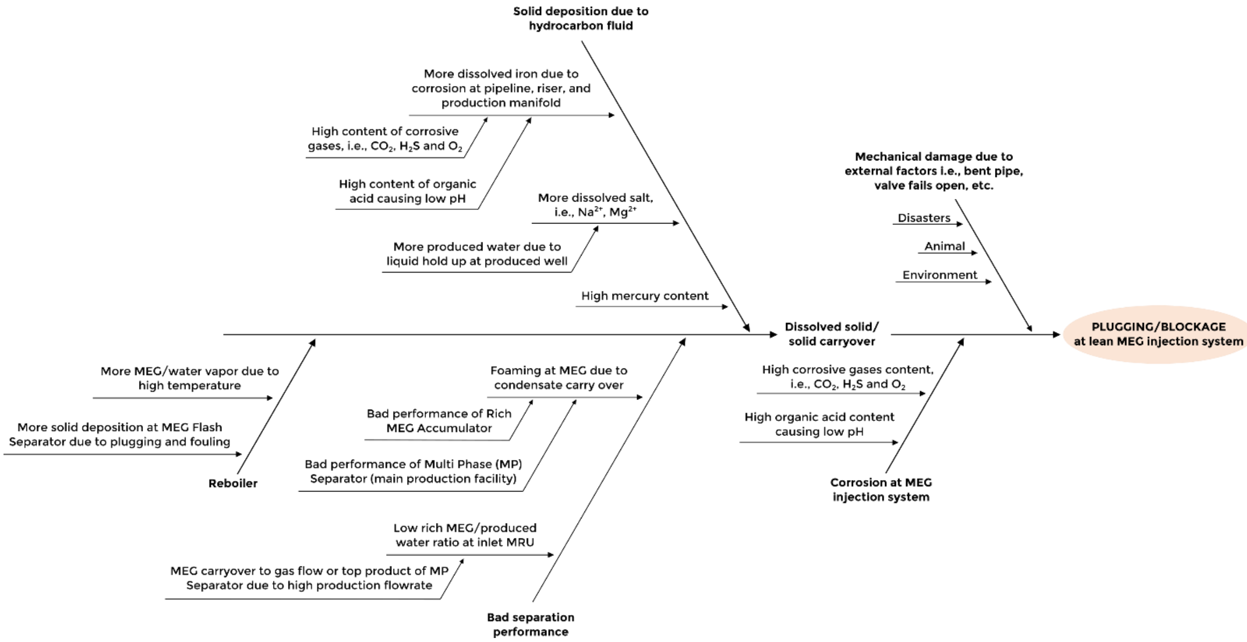

Figure 2. Fishbone Diagram of Plugging Problem at Lean MEG Injection System.

A fishbone diagram as shown in Figure 2 was chosen in this study to analyze the root cause of plugging in the lean MEG injection system. In general, plugging is caused by dissolved solids being carried from the MRU feed line (rich MEG) to the lean MEG injection line due to process distortion and disruption along the regeneration process. These will subsequently settle in the injection system at favorable pressure and temperature. Therefore, the number of these particles can be monitored by analyzing the level of cleanliness in the injection line. Thus, the cleanliness level can be used as a reference for the possibility of plugging determination

3.2 Possibility of plugging prediction

Several algorithms were applied to the training set using cross-validation with a total of 10 folds. The K-Fold CV is usually used because it can reduce computation time while maintaining the accuracy of the estimate for each algorithm. The best algorithm was then tested on the previously separated testing data. Apart from accuracy, the F1 score was also used to evaluate the performance of the model as shown in Figure 3.

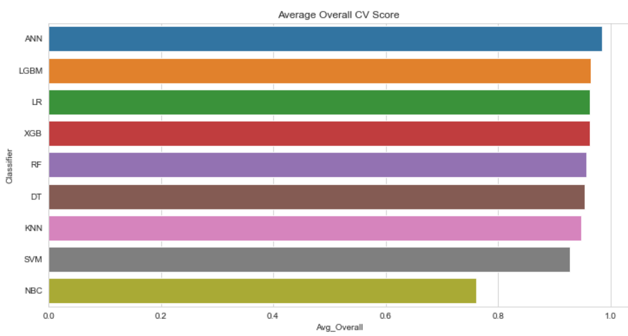

Figure 3. Average Overall Cross-Validation Score

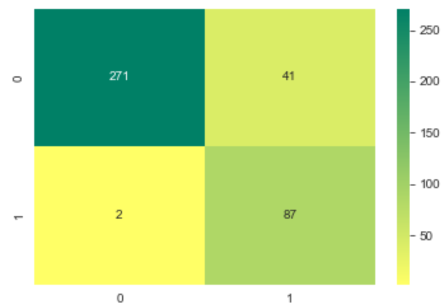

Figure 4. Confusion Matrix of ANN Application on Testing Data

The Artificial Neural Network (ANN) model has the highest accuracy among other algorithms at 0.9847 or 98.47%. This algorithm then was selected and applied to the testing data to ensure its performance when finding new data that has never been trained before. The ANN model provides accuracy and F1 score of 0.8928 (89.28%) and 0.8018 (80.18%) respectively with a confusion matrix which can be seen in Figure 4.

3.3 Application of the ANN model

The ANN algorithm was applied to all data along the production lifetime of Field K between 2017 and 2022 to predict when plugging might occur in the MRU system. This prediction was done because the forecasting process data at the end of the production period is not available. Moreover, since there is an oddity in the last data of produced water flow rate, the forecasting using machine learning for process data will give less accurate results. The result of the ANN application along the production lifetime of Field K can be seen in Figure 5.

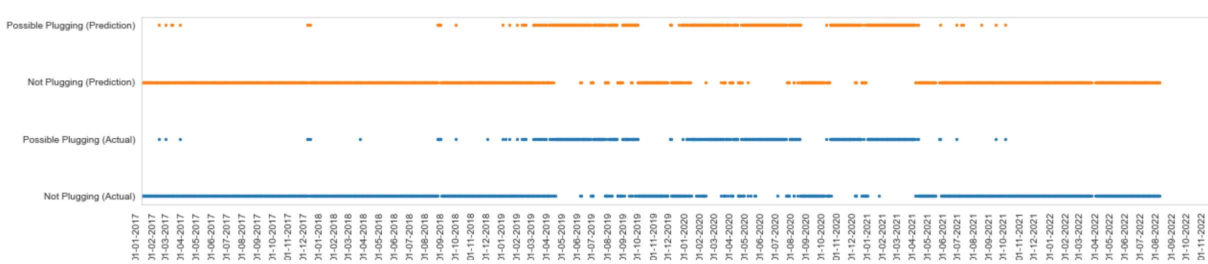

Figure 5. Prediction of Possible Plugging and Not Plugging during Production Lifetime

The plugging likely occurred in April-September 2019, January-August, November-December 2020, and January-April 2021. During these months, it is highly suggested to operators monitor the cleanliness level regularly and strictly. MEG fresh makeup must be prepared well and injected more often during these months to lower the cleanliness level to the company's criteria. Methanol is recommended as a second safety layer if the MEG injection flow rate is zero. All instruments and equipment are ensured to operate properly so that they can be identified clearly if there is a deviation in operating conditions.

4 Conclusions

This paper established a method to find the correlation model between cleanliness and process parameters using machine learning (ML). The cleanliness level based on root cause analysis can represent the possibility of plugging (1) and not plugging (0). The nine popular algorithms of the supervised learning approach are selected to perform the correlation between target variables and predictor variables. The accuracy and F1 value of all algorithms are above 90% except for naïve Bayesian classification (NBC). Artificial Neural Network (ANN) is the best algorithm with the highest overall accuracy. This paper suggests that the ML method can be used to predict the plugging possibility that occurs at a certain time. The methodology used in this paper can be beneficial for companies in forecasting plugging issues by training the model using its historic data. Therefore, it can help operators in making decisions regarding MRU operation, monitoring, and maintenance strategies.

Although this paper already has 2003 sets of imaginary data with five parameters, these data are not enough to achieve an accurate prediction of the cleanliness level. Some other parameters should be considered such as rich and lean MEG flow rate, fresh MEG make-up, glycol concentration, temperature of pipeline and boiler, pH level, total dissolved solids (TDS), corrosive gas content, solid content, and other chemical inhibitor flow rate. Moreover, machine learning methods rely on the quality and number of datasets. Therefore, actual data will be considered and introduced in the next research to further improve the accuracy and application scope of the prediction model.

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