Deteksi Stuck Pipe pada Operasi Pengeboran Geothermal Sumatera Utara Menggunakan Artificial Neural Network

Stuck Pipe Detection for North Sumatera Geothermal Drilling Operation Using Artificial Neural Network

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Abstract. *One of the most common problems encountered during geothermal drilling operations is stuck pipe. The risk of stuck pipe is higher in geothermal drilling operations since geothermal drilling targets the lost circulation zone at reservoir depth. The stuck pipe problem can cause a significant increase in drilling time and costs. The cost of a stuck pipe includes the time and money spent on extracting the pipe, fishing the parted BHA, and the effort required to plug and abandon the hole. Therefore preventing stuck pipes is far more cost effective than the most effective freeing procedures. Many researchers are working to identify the symptoms to reduce the risk of a stuck pipe. Due to the complexion of stuck pipe's symptoms and indicators, some researcher proposed artificial intelligence (AI) as the tool to predict stuck pipes. Although researches have been made to build systems employing artificial intelligence (AI) to avoid stuck pipe occurrences in oil and gas drilling operations, few works have been done for geothermal drilling operations. This paper describes a study that employed Artificial Neural Networks (ANN) approaches to predict stuck pipe incidents. Field data were collected from 6 geothermal wells drilled in North Sumatera fields. ANN was used to construct models to forecast stuck pipe incidents. The investigation found that ANN showed good performance with 84% accuracy and 74% recall for the limited training dataset. These ANN approaches provide good predictions that can help increase response time and accuracy in preventing stuck pipes.*
Keywords: *Stuck pipe, Geothermal drilling, Machine Learning, Artificial Neural Networks*

INTRODUCTION

The cost of drilling in a geothermal field can be more expensive than onshore oil and gas drilling due to the requirement for special tools and techniques for harsh and downhole conditions and also large tubular are required for large flow rates[1]. And this high cost can be increased because of the hole problem such as a stuck pipe.

Stuck pipe is a common problem in geothermal drilling operations. Since the target of geothermal drilling is lost circulation zones at reservoir depth, the chance of getting stuck pipe events becomes higher. The consequences of a stuck pipe can cause not only Non-Productive Time (NPT) but also an extra cost due to fishing out the parted Bottom Hole Assembly (BHA), lost-in-hole tools, plug and abandon (PnA) and sidetrack. In most recent cases in Indonesia, stuck pipe incidents accounted for 10–30 percent of total NPT – which implies, up to hundred thousand dollars undesired cost for prolonged total drilling time, the replacement cost of equipment lost, and curative action to resume the operation [2]. The same issue also occurs in geothermal drilling in Kenya and Iceland where the main NPT contributor is stuck-pipe events [3].

The prevention of stuck pipes is critical. Preventing of stuck pipes is far more cost-effective than even the most effective freeing procedures [4]. To prevent stuck pipe problems, it is important to detect and predict the symptoms earlier, so the right preventive action can be taken. If a model or technique can predict stuck pipe earlier and driller can prevent their occurrence, the costs and time would be reduced.

Many researchers are working to identify the symptoms and their associated consequences to predict and prevent stuck pipe. Arnaout et al demonstrated how sensor measurements can be analyzed using visual analytics techniques (classification) to identify "Stuck Pipe"[5]. This method uses visual analytics using statistics but unfortunately no learning in the process. Guzman et al. address the stuck pipe problem by analyzing Torque and Drag (TnD) and equivalent Circulating Density (ECD) [6]. Salminen et al. proposed that adding hydraulics data such as standpipe pressure and flow rate to the analysis will improve the reliability [7]. They proposed a method called the Stuck-Pipe-Risk (SPR) log method to predict stuck pipes. This method uses 2 leading indicators, Method Vs Actual (MVA) and Rate of Change (ROC). MVA analysis determines the deviation of the Hydraulics and Torque and Drag (T&D) model with the actual data. Rate of Change (ROC) analysis identifies rapid changes in key parameters. The SPR method showed to have good performance to give a warning for stuck pipe events but this method does not include learning method for the program.

From the existing research, it appears that there is no mathematical equation and analytical modeling tool that can be used to predict stuckpipe incidents using drilling parameter. This is the reason why some researchers use artificial intelligence to predict stuck pipe. Artificial Intelligence can be used to solve complicated problems that cannot be solved using mathematical equation or analytical modeling [8]. Artificial Intelligence has been used widely in Petroleum Industry such as pore pressure prediction, flowing bottom hole pressure presiction, corrosion rate prediction and the oil and gas production profiles prediction [9]–[12]. Some researchers also used artificial intelligence in oreder to predict stuck pipe in petroleum industry. Abbas et al. use a machine learning algorithm for dealing with the stuck pipe in an oil environment [4]. Chamkalani et al. classify the stuck pipe type based on LSSVM analysis [13]. Alshaik et al. compared Decision Tree, Support Vector Machine and Artificial Neural Network for detecting stuck pipe incidents [14].

Although many observations have been made to design a system for avoiding stuck pipe incidents in oil and gas drilling operations using artificial intelligence (AI), there have been few works established for geothermal drilling operations. The goal of this project is to design an ANN model to predict stuck pipe in geothermal drilling operations based on historical data from a specific geothermal field.

METHODOLOGY

In this research ANN will be used as a prediction tool to predict stuck pipe based on the drilling parameter. The methodology of this research can be seen in figure Figure 1. Pyton software was used in this research.

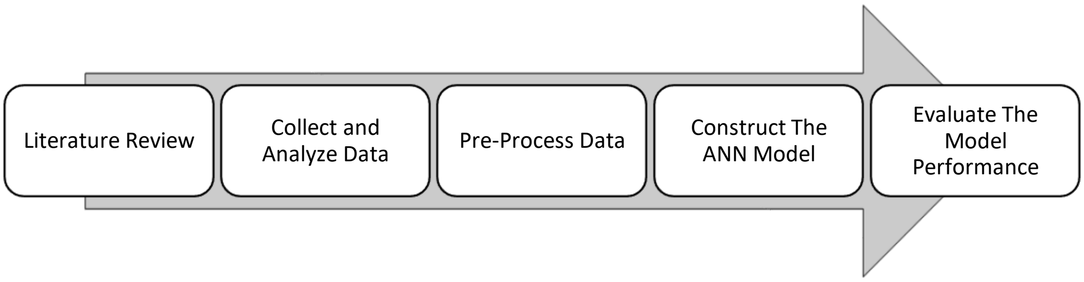

Figure 1. *Research Methodology*

Research begins with a literature review on stuck pipe problems in drilling operations and artificial neural network. Paper studies related to the stuck pipe are carried out to determine the important parameters that have a strong correlation with the stuck pipe event.

The next step is collecting data from the geothermal well. A sufficient amount of data is needed to build an Artificial Neural Network Model. Daily Drilling Report (DDR), Final Well Report (FWR) and mud logging data are acquired from geothermal drilling operation. Mud logging data was measured in real-time during drilling operations (measured every ten seconds) and QC has been done by the mud logging company. Data that is used in this research are 5 wells data from pad T in the North Sumatera field. The drilling parameters that will be used as the input parameter to predict stuck pipe are:

a. Torque (TRQ). The value of of torque applied to the drillstring
b. Hookload (HKLD). The value of of drillstring weight
c. Standpipe pressure (SPP). The value of internal pressure inside the drillstring
d. Rotation per minute (RPM). The value of rotation applied to the drillstring
e. Weight on Bit (WOB). The value applied to the drilling bit (i.e lowest part in drillstring that used to crush the formation)
f. Gallon per Minute (GPM). The value of fluid pumped into the drill string
g. Rate of Penetration (ROP). The value of drilling speed value of a well is usually in meter per hour or feet per hour unit.

Then the data are pre-processed by conducting [15]:

- Data Normalization (Feature scaling)
  Feature scaling is a process to normalize all data & features so all have the same interval to prevent any feature from affecting the model more than other features. This process also helps to conduct statistical analysis of the data. The “Min-Max” method is used for the feature scaling to convert all data within zero to one interval.

- Data Split
  The data was split into train and test data to evaluate the performance of the model after training. Train data will be used to train the model while the test data will be used to test the model once the training is completed. This function will split the data randomly, which means the result of the algorithm could be different every time the program is run, to prevent this to happen random state parameter is used.
- Data Balancing
  In general, most of the data gathered in observation is not balanced which could affect the training process of the classifier model, thus data processing is needed to balance the class in the training data. The main purpose of data balancing is to increase the frequency of the minority class or reduce the frequency of the majority class so all classes will have a similar frequency of data
- Feature Selection
  Feature selection is used to rank the features that will be used to train a model. The aim is to reduce the number of features for the model based on the rank, this will reduce the dimension of the model thus reducing the resources requirements.

After the data is pre-processed then the ANN model is constructed. MLPClassifier from scikit-learn library is used to build a model of Perceptron Multi-layer which use a backpropagation algorithm. The topology of the ANN model is defined by choosing the number of hidden layers, the number of neurons in each hidden layer, number of iterations or epochs. Sensitivity of those parameters will be conducted to define the best topology for the ANN Model.

The last step is to choose the topology of the ANN model that produces the best performance. A confusion matrix is one of the tools used to evaluate the performance of the model, equation and values in the confusion matrix are [16]:

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

- True Positive (TP): number of predictions where the classifier correctly predicts the positive class as positive.
- True Negative (TN): number of predictions where the classifier correctly predicts the negative class as negative.
- False Positive (FP): number of predictions where the classifier incorrectly predicts the negative class as positive.
- False Negative (FN): number of predictions where the classifier incorrectly predicts the positive class as negative.

This step aims to get the best recall and accuracy percentage to minimize miss identification of stuck pipes, where a false-positive condition is preferable to a false-negative condition.

RESULTS AND DISCUSSION

Data that are used in this research is a time-based data, which measured every ten seconds. 331,988 Raw data are extracted from customer database in ASCII format (Figure 2) and will be convert to csv for training and test. The statistic of the input data can be seen in Table 1.

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Date-Time          Section BlockPos         BitDepth          DrillDepth      ROPad    ROPah    ROPa1    Hkld     WOB      Torque   RPMs     RPMm     RPM      SpPress  CsPress  MudFlowIn         MudFlowOutp
           (in)    (m)      (m)      (m)     (m/hr)   (m/hr)  (m/hr)   (klb)  (klb)    (lb.ft)                             (psi)    (psi)    (gpm)             (°C)     (°C)     (ppg)    (ppg)    (ppg)
01/19/2020 0:00:00          12.25    24.53   2038.15  2048                             59.35    0        0        0        0        0        0        0        0        0        32       38       8.4      8.4
01/19/2020 0:00:10          12.25    29.59   2038.15  2048                             58.99    0        0        0        0        0        0        0        0        0        32       38       8.4      8.4
01/19/2020 0:00:20          12.25    32.79   2038.15  2048                             59.42    0        0        0        0        0        0        0        0        0        32       38       8.4      8.4
01/19/2020 0:00:30          12.25    32.52   2038.15  2048                             59.49    0        0        0        0        0        0        0        0        0        32       38       8.4      8.4
01/19/2020 0:00:40          12.25    32.52   2038.15  2048                             59.49    0        0        0        0        0        0        0        0        0        32       38       8.4      8.4
01/19/2020 0:00:50          12.25    32.52   2038.15  2048                             59.49    0        0        0        0        0        0        0        0        0        32       38       8.4      8.4
01/19/2020 0:01:00          12.25    32.52   2038.15  2048                             59.49    0        0        0        0        0        0        0        0        0        32       38       8.4      8.4
01/19/2020 0:01:10          12.25    32.52   2038.15  2048                             59.49    0        0        0        0        0        0        0        0        0        32       38       8.4      8.4
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Figure 2. *Raw Data*

Table 1. *Data Statistic*

	Torque (lb.ft)	Hookload (klb)	Standpipe pressure (psi)	ROP (m/hr)	Rotation per minute (rpm)	Weight on Bit (klb)	Mud Flow (gpm)
Mean	2.2	70.6	518.8	21.2	63.3	4.2	346.3
Std.	3.6	52.6	699.7	30.8	87.6	11.4	437.0
Min.	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Max.	32.0	1519.5	2692.7	151.0	4286.0	3032.2	3963.0

The output data or the target of the Artificial Neural Network Model is the stuck pipe event. The stuck pipe event is labeled based on report on Daily Drilling Report. If the stuck pipe is occurred than the data will be labeled as 1, and if there is no stuck pipe it will be labeled as 0. Then data cleaning was conducted by deleting rows with missing parameter or abnormal data to prevent contamination during model training. Initial data balancing was done by cutting the data to be around the time when the stuck pipe incident happens (six hours before and one hour after). Training data will be using "Well T-02 T-04 T-09.csv" that combines T-02, T-04, T- and T-09, testing data will be using "Well T-03L3 T-07.csv" that combines T-03L3 and T-07,

Before training the model, the aforementioned sensitivity analysis was done that concerns number of hidden layers, the number of neurons in each hidden layer, number of iterations or epochs in order to be aware of the optimum values of those parameters. The ANN Model with 20 neurons and 8 layers under sampler balancing produced the greatest results (Figure 3), while the ANN Model with 20 neurons and 7 layers produced the best results above sampler balancing (Figure 5). The accuracy and recall (normal status) results are quite low while employing under sampler balancing (Figure 4), which is normal because ANN requires more data to perform better. When using under sampler balancing to a limited dataset, the ANN will learn less and consequently perform worse than when using over sampler balancing. As shown in Figures 4 and 5, adding neuron reduces the volatility of the training outcomes' accuracy.

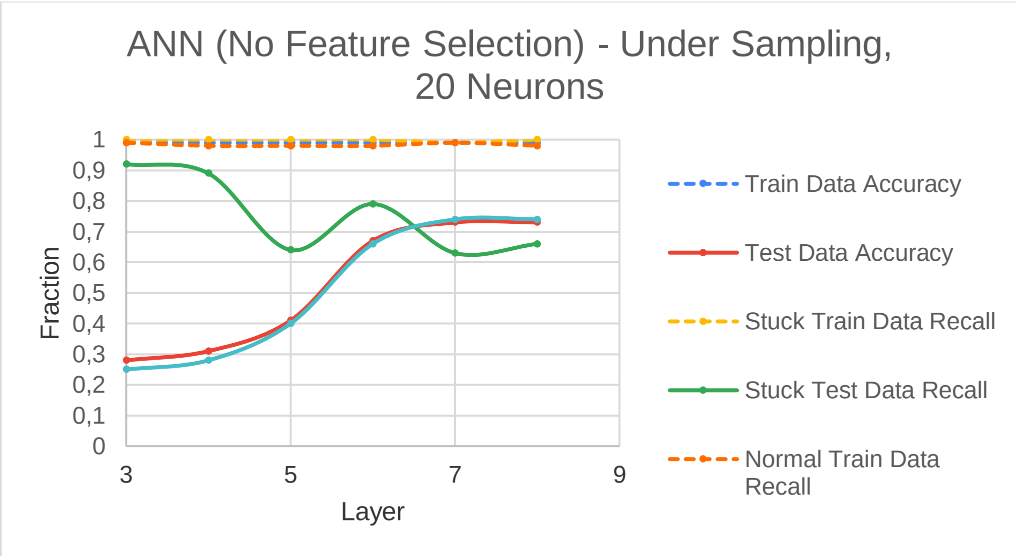

Figure 3. *ANN Under Sampler 20 Neuron*

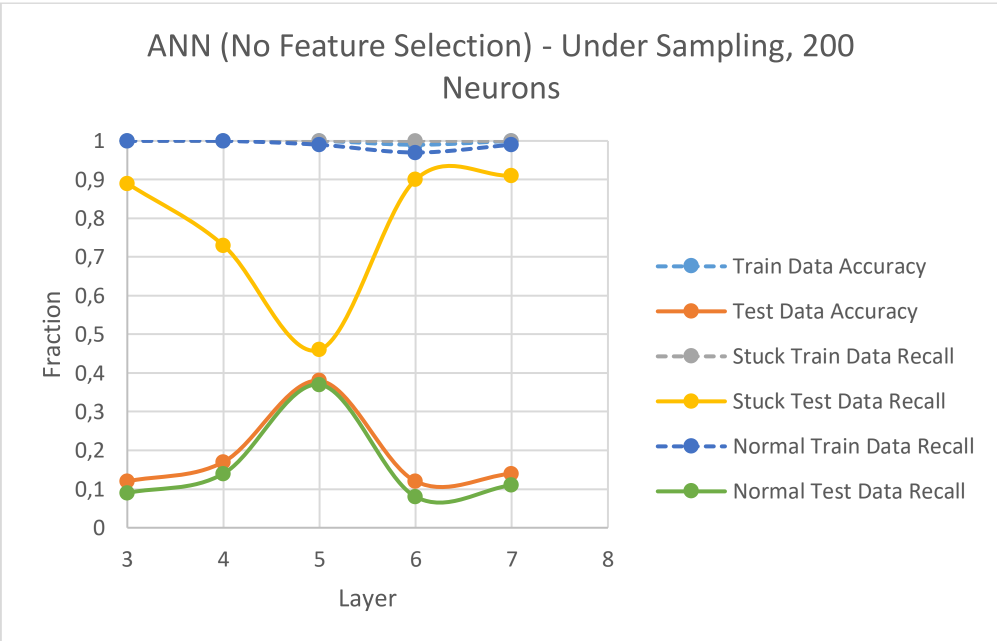

Figure 4. *ANN Under Sampler 200 Neurons*

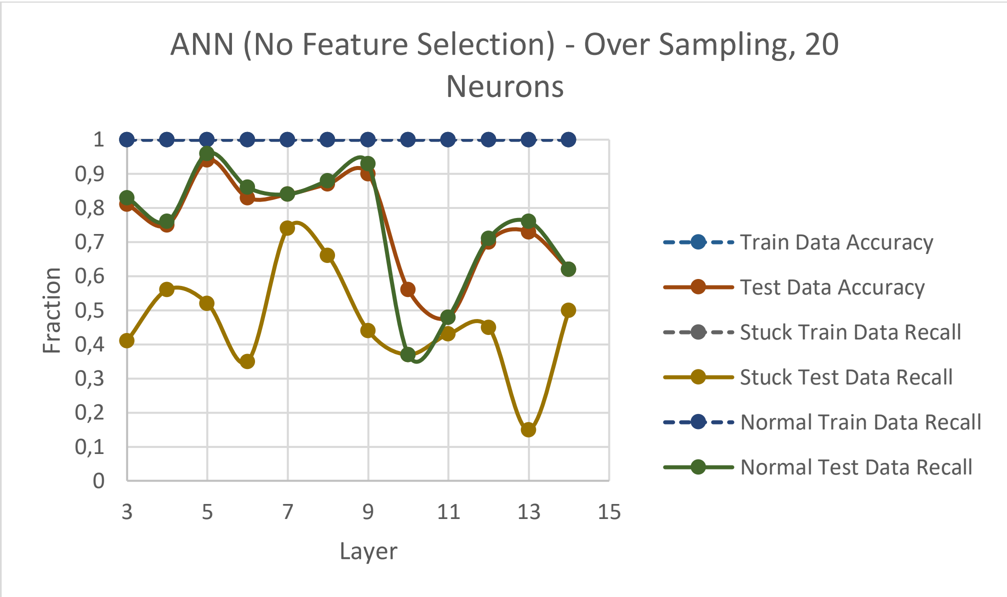

Figure 5. *ANN Over Sampler 20 Neuron*

Based on the model's performance evaluation above, the ANN model with 7 hidden layers, 20 neurons and oversampling method yields the best result to predict stuck pipe, 84% accuracy and 74% recall.

CONCLUSION

The ANN Model can be used to predict stuck pipe in Geothermal Well in pad T in the North Sumatera field with 84 percent accuracy and 74 percent recall. An improvement in ANN performance is expected if we can increase the training dataset because ANNs rely on a large amount of data to train the model and determine the optimum weight for each neuron connection. Although the model's performance in geothermal operations was lower than in oil and gas operations, it still demonstrated good performance and potential for use in geothermal operations, therefore more research is required to improve the model's performance and continue the pilot project in geothermal operations.

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