APPLICATION OF ANN-BASED DECISION MAKING PATTERN RECOGNITION TO FISHING OPERATIONS

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ABSTRACT

Decision making is a crucial part of fishing operations. Proper decisions should be made to prevent wasted time and associated costs on unsuccessful operations. This paper presents a novel model to help drilling managers decide when to commence and when to quit a fishing operation. A decision making model based on Artificial Neural Network (ANN) has been developed that utilizes Pattern Recognition based on 181 fishing incidents from one of the most fish-prone fields of the southwest of Iran. All parameters chosen to train the ANN-Based Pattern Recognition Tool are assumed to play a role in the success of the fishing operation and are therefore used to decide whether a fishing operation should be performed or not. If the tool deems the operation suitable for consideration, a cost analysis of the fishing operation can then be performed to justify its overall cost.

KEYWORDS

fishing operation, decision making, pattern recognition, Artificial Neural Network

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1. INTRODUCTION

Fishing is the process of removal of equipment that has been stuck or lost in the wellbore during drilling, casing, or completion operations. The need to remove lost equipment from the borehole is as old as the drilling industry. The name derives from the early periods in which a simple hook attached to a line was lowered into the borehole to recover lost equipment or fish in the wellbore. Operator error, surface and down hole equipment decline, and improper hole cleaning are major causes of fishing jobs. It is clearly obvious that, when dealing with fish that are lost in the borehole, the selection of fishing tools and fishing procedures is very important, but the main point is that only a minor part of the personnel involved in fishing jobs thinks on when to quit fishing.

A survey including 12 % of drilling rigs in the United States showed that more than 16 % of those rigs were involving fishing operations (**Short, 1981**). The same survey done by this study has indicated that approximately 32 % of the rigs drilled in south western oil fields of Iran involved fishing operations. This huge amount of fishing operations definitely spend considerable cost and time and should be reduced as much as possible.

Due to a lack of rigorous policy and procedures to follow during decision making processes, drilling personnel tend to commence a fishing operation under any condition. In some cases, they also spend a significant amount of unnecessary time working on fish that in most cases should not have been attempted to begin with. Failed attempts jeopardize significant portions of the rig time and, in turn, cost hundreds of thousands of dollars.

In 1980, G. Harrison proposed a decision tree strategy to minimize losses during fishing operations. The method he devised closely follows the theory of utility developed by John von Neumann and Oskar Morgenstern (**Harrison, 1982**).

Keller et al. (1984) studied statistics of using spotting fluids to free stuck drill pipes, as well as the economics and statistics of drill string fishing operations. Their analysis resulted in a method that could be used to estimate an economic fishing time.

Later, **Schofield et al. (1992)** extended the method introduced by **Keller et al. (1984)**. Their method was based on field experience and they assumed that the success of the fishing operation was strongly dependent on time, such that there was a substantial chance of freeing a stuck pipe if immediate action was taken. Considering this fact, they proposed the Weibull cumulative density function as a time-dependent probability to calculate the probability of a successful fishing operation.

In 1993, Texaco developed an operational procedure for fishing operations. A decision making flow chart was formulated to handle stuck pipes based on risk and economical analyses. Through a trial-and-error procedure, important wellbore parameters such as hole angle, hole size, and mud weight were found to affect the chance of freeing stuck pipes. These wellbore parameters were then used to calculate the probability of freeing stuck pipes (**Shivers and Domangue, 1993**).

This paper aims to present a decision making model for handling and reducing the risk associated with fishing operations. Instead of a trial-and-error manipulation of fishing incidents, which has been proposed in other studies, a Pattern Recognition Tool based on Artificial Neural Network (ANN) is used for analysis. In addition, the proposed model has the advantage of considering past experiences, wellbore conditions, and the economics of the fishing operation all at once. A data set of 181 fishing incidents, including important wellbore parameters as inputs and success or failure of those attempted retrievals as outputs are used to train the ANN-Based Pattern Recognition Tool. This tool can then decide whether a fishing operation should be started or not, based on the borehole conditions. As is the case with any fishing operation, if the model decides a particular wellbore is suitable to initiate a fishing operation, then costs of operation should be rigorously calculated in order to find an economic fishing time.

2. MATERIALS AND METHODS

2.1 Review of ANN-Based Pattern Recognition Tools

Pattern recognition is an important attribute that has great facility in a variety of engineering and other scientific disciplines. A pattern could be a fingerprint image, a handwritten cursive word, a human face, speech signal, or a decision. It is the study of how machines can learn to distinguish patterns of interest from their background, and for instance make sound and reasonable decisions about the categories of the patterns (Basu et al., 2010).

Pattern recognition can be implemented by using an ANN that has been trained accordingly. During method development, the network is trained to associate outputs (successful or failed fishing incidents) with input patterns (wellbore parameters). When the network is used, it identifies the input pattern and tries to output an associated pattern. The power of neural networks appears when a pattern that has no output associated with it is given as an input. In this case, the network gives the output that corresponds to a taught input pattern that is least different from the given pattern.

The objective of this paper is to introduce an ANN-Based Pattern Recognition Tool as the best possible way of considering past experience of fishing and wellbore conditions, in order to make sound decisions in fishing operations.

2.2 Fishing data set

One of the most fish-prone oil fields in the southwest of Iran was selected for this study. Frequent fishing jobs for this area seem to be associated with inadequate decision making because there were several records on attempts to release a stuck pipe or recover a parted bottom

hole assembly for more than two months.

Daily drilling reports of 107 wells were carefully reviewed to collect a data set of 209 fishing records. After collecting the fishing records, only those incidents related to stuck, twisted off, and parted drill string or bottom hole assemblies were selected to be included in the model training (181 out of 209). Fishing incidences due to small junk, like cone bits, have been ignored because these types of junk are recovered or milled most of the time.

3. RESULTS AND DISCUSSION

3.1 ANN-based decision making pattern recognition tool

3.1.1 Preparing input data

Table 1 show a statistical summary of important wellbore parameters which are used for developing ANN-Based Decision Making Tool. Schofield et al. (1992) first proposed that wellbore diameter, mud weight, depth of the fish, and deviation of the well play a considerable role in any fishing attempts. They assumed that the chance of success in recovering a fish is directly proportional to the deviation of the wellbore. The same relationship between chance of fishing success, mud weight and hole diameter was also assumed. In the case of depth, an inverse proportionality was suggested based on field experiences.

In addition to the four parameters above, in this study, it is assumed that formation and fish type also play a role in the fishing operation. In Table 2, frequency and recovery history of fishing in different types of formations is summarized. Marl, salt, sandstone, carbonates, and thin intervals of shales that are dispersed in the sandstone and carbonate formations comprise the geological structure of the field of study. Sandstone and

Table 1. Statistical summary of important wellbore parameters for developing ANN-Based Decision Making Tools.

Parameter	Unit	Maximum Value	Minimum Value
Wellbore Diameter	Inch	26	4.125
Depth	Meter	5210	432
Mud Weight	Pounds/ft ³	162	55
Deviation	Degree	92.3	0
Formation Type	_____	89.19	75.00
Fish Type	_____	87.5	75.4

Table 2. Fishing history in different formations of the field of study.

Formation Type	Fishing Frequency, %	Recovery, %
Sandstone and Carbonates	28.73	75.00
Marl	30.38	83.64
Salt	40.89	89.19

Table 3. History of stuck pipe and twisted off incidents in the field of study.

Fish Type	Frequency, %	Recovery, %
Twist off	33.70	75.40
Stuck pipe	66.30	87.50

carbonate formations are relatively inactive compared to sticky and active formations like marl and other salty formations. In addition, the presence of shaly intervals within these formations resulted in their being grouped into one class. There are also two other groups assigned for sticky and active formations like marl and salty formations. As shown in Table 2, there is a different fish recovery for each group. For instance, the presence of troublesome shales reduces the chance of fish recovery in the first group. It should be noted that the percentage of fish recovery for each group is used as a quantitative input parameter for the ANN-Based Decision Making Pattern Recognition Tool.

The last input parameter introduces type of fish in the decision making tool. Since the fishing procedure is different for stuck and twisted off pipes, and due to the difference in recovery percentage (Table 3), two groups are assigned for each one. Again, the percentage of fish recovery is introduced as an input parameter to the model network.

3.1.2 Normalizing input data

Normalizing data is an important step before introducing input data to any neural network. It transforms input data with different ranges into

one similar range and allows for easier and faster model training. Equation 1 is a common method to change the range of input data into 0 and 1.

$$X_{\text{new}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (1)$$

3.1.3 Output data

Qualitatively, the output of any fishing operation is either considered to be a failed or successful attempt. In order to introduce these two terms into the network, the character 1 is assigned to the successful fishing attempts, and the character 0 is attributed to failed ones. So for each set of six input entries, there is an output set of two entries. In the case of successful attempts, the first entry is 1 and the second entry is 0. For failed attempts, one and zero are interchanged in the output set.

3.1.4 Design and training of the Pattern Recognition Tool

The Decision Making Pattern Recognition Tool is designed by arranging a set of input vectors and wellbore parameters, as columns in a matrix as shown in Figure 1. Another set of target vectors, i.e., failed or successful attempts, is then arranged,

Table 4. Characters used to introduce successful and failed attempts to the network.

Input Data	Input Character
Successful Fishing Attempt	$\begin{bmatrix} 1 \\ 0 \end{bmatrix}$
Failed Fishing Attempt	$\begin{bmatrix} 0 \\ 1 \end{bmatrix}$

Figure 1. Schematic of ANN-Based Decision Making Pattern Recognition.

so that they indicate the classes to which the input vectors are assigned. As previously mentioned, target vectors have 2 elements, where for each target vector, one element is 1 and the others are 0. Table 4 better represents the target vectors for successful and failed attempts.

In this study, a Decision Making Pattern Recognition Tool is developed that is a feed forward network with tan-sigmoid and pure-line transfer functions in the hidden and output layers, respectively. The network uses 15 neurons in the hidden layer and 2 neurons in the output layer. A Scaled Conjugate Gradient algorithm is then used for training the network. All the input and output data are randomly divided into three sets: 60 %

(109 incidents) are used for training network and 20 % (36 incidents) are used to validate that the network is generalizing and to stop the training before overfitting occurs. The last 20 % (36 incidents) are used as a completely independent test of network generalization.

3.1.5 Pattern Recognition Tool performance

Confusion matrices are typically used for validating Pattern Recognition applications. Figure 2 represents confusion matrices for training, validation, testing, and all of the data together. Each row of the matrix represents the cases in a predicted class, while each column represents the cases in an actual class. One benefit of a confusion

Figure 2. Confusion matrices for the developed ANN-Based Decision Making Pattern Recognition Tool.

matrix is that it is easy to see if the developed network is confusing two classes. Considering the

Figure 3. Receiver Operating Characteristic (ROC) for training data set.

Figure 4. Receiver Operating Characteristic (ROC) for validation data set.

Figure 5. Receiver Operating Characteristic (ROC) for test data set.

Figure 6. Receiver Operating Characteristic (ROC) for the entire data set.

test confusion matrix, the developed Decision Making Pattern Recognition Tool predicts for 36 fishing jobs whether each case is successful or a failure. It correctly predicted 25 cases as successful fishing attempts and 3 cases as failed attempts; however, the model also incorrectly predicted 2 successful jobs as failed ones, and 6 failed attempts as successful ones.

Figures 3 through 6 present Receiver Operating Characteristic (ROC) curves for training, validation, test data sets, as well as the entire data set. The solid and dashed lines in each axis represent the ROC curves for each of the two output classes. The ROC curve is a plot of the true positive rate (sensitivity) versus the false positive rate as the threshold is varied. A perfect test would show points in the upper left corner, with 100 % sensitivity and 100 % specificity.

3.2 New Decision Making Flow Chart

The Developed Pattern Recognition Tool is able to incorporate a decision making flow chart for the case of fishing operations as shown in Figure 7. In the case of any fishing incident, the first step is to find those input parameters in the ANN-Based Pattern Recognition Tool. The tool then decides whether the fishing operation should be commenced or not. If the answer is negative, alternatives such as sidetracking, completion, or abandonment should be decided upon immediately (**Short, 1981**). In the case of a positive response by the Pattern Recognition Tool, it is

Figure 7. Decision making flow chart for fishing operation.

recommended to evaluate the Economic Fishing Time (EFT) using equation 2 without considering the probability of the success.

$$EFT = \frac{KHC}{DFC} \quad (2)$$

Where KHC stands for "Known Hole Costs", which includes the cost of the fish, plus the cost of redrilling to the original depth; DFC stands for "Daily Fishing Cost" (Keller et al. 1984).

Retrieval of the fish should be attempted only up to the estimated EFT. Beyond that limitation, alternatives should be applied to prevent excessive costs of the fishing operation.

4. CONCLUSIONS

This paper introduces the capability of an ANN-Based Pattern Recognition Tool as a logical and convenient method in decision making. It is especially suitable to be applied in fishing operations in which past experiences are key in decision making processes. Regarding the proposed methodology in this paper, it should be noted that, although the accuracy of developed Pattern Recognition Tool is not 100 % perfect, as can be observed in the Receiver Operating Characteristic (ROC) curves, it is still much more accurate and logical than some of the trial-and-error analysis proposed by previous investigators. The amount of error within the predictions made by developed Decision Making Pattern Recognition Tools is most likely due to the lack of sufficient data and could be further improved with a larger data set. New fishing incidents should be added to the current data base such that the model accuracy could be further improved.

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NOMENCLATURE

DFC - Daily Fishing Cost, USD/hr
EFT - Economic Fishing Time, hr
KHC - Known Hole Cost, USD
X - Input Parameter
 X_{new} - Normalized Input Parameter
 X_{max} - Maximum Input Parameter
 X_{min} - Minimum Input Parameter

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