Application of fuzzy logic for stuck pipe prevention purposes on oil wells drilling operations

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Abstract. The drilling of oil wells represents one of the most challenging activities in the oil and gas industry. In an environment surrounded by uncertainties, one of the most common problems is the stuck pipe, which results in increases in the cost of building the well and in non-productive time. Considering that factors such as safety and costs are directly related to the decisions made during operations, the adoption of tools that help the operator to make the best decisions is highly desirable. In addition, the large amount of information available to the operator requires its due analysis in real time in order to offer the diagnosis of anomalies. Artificial intelligence techniques such as artificial neural networks, decision trees and support vector machines have been used to detect stuck pipe. These strategies, however, have efficiency conditioned to the specific characteristics of the available data set. Alternatively, this work presents an algorithm for preventing stuck pipe using fuzzy logic. Throughout the paper, the stuck pipe problem and its impacts will be presented, the characteristics of fuzzy logic and its application to the case under study, the results obtained from the application to an oil well data and, finally, the job conclusions.

Keywords: stuck pipe, drilling, wells, fuzzy, artificial intelligence.

1 Introduction

The activity of drilling for oil wells contains a large part of the challenges and criticality in the oil exploration and production chain. It is a high-risk activity, especially in an offshore environment, subject to various impacts during the well construction process, (Tavares [1], Elmousalami et al. [2]). Although the current stage of technology provides a large amount of information about the process, whether through a database or even in real time, the use of tools capable of analyzing such data volume and providing an accurate diagnosis of possible anomalies represents a great opportunity to improve the process, giving robustness, security and reliability to it.

It should also be noted that the costs required for drilling oil wells (involving the drilling rig daily rate, equipment, among others) are high (Heinze et al. [3], Ivan et al. [4]), which promotes interest in the effectiveness and efficiency of the process, either through diagnostics that enhance the operator's performance and/or that reduce NPT (non-productive time) values, Tang et al. [5].

One of the common problems while drilling oil wells is the stuck pipe, which comes from factors such as: hydraulic packer, well collapsing, pipe sticking and improper cleaning of the well anular, Tavares [1]. This phenomenon is related to the increase in the non-productive time of operations, and the cost of actions in response to this phenomenon, aiming at the release of the drill string, Naraghi et al. [6]. In fact, the consequences of this anomaly range from rising operating costs, Toreifi et al. [7], even more severe problems, such as loss of the drill string or the whole well, leading to its abandon, Shadizadeh et al. [8].

In this context, in Ivan et al. [4] an intelligent web system for stuck pipe detection due to hydraulic packer is proposed. Using a multilayer perceptron (MLP) neural network, with the following inputs: stand pipe pressure, hook load, string torque and rate of penetration, the system presents four alerts to the operator, normal operation or alarm levels between 1-3. The level 3 alarm indicates a high risk of stuck pipe due to hydraulic packer.

By other perspective, Shadizadeh et al. [8] presents the detection of stuck pipe caused by differential pressure, also through a neural network using as input data, however, drilling fluid parameters and well geometry data. The author segments the problem by addressing dynamic (drilling fluid circulation) and static (non-circulating) situations, proposing a neural network for each situation. The models give the stuck pipe occurrence probability as their output.

The combination of artificial intelligence techniques is also applicable in the detection of the anomaly under study. Toreifi et al. [7] compares the use of artificial neural networks (ANNs) and support vector machines (SVMs) for this purpose, based on data from wells in the Marun field in Iran.

Among other aspects, the works previously described share the use of large datasets. In fact, the effectiveness of machine learning algorithms (including ANNs) depends strictly on the size of the training database (Heinze et al. [3], Shadizadeh et al. [8]). In addition, the use of neural networks for the purpose of detecting stuck pipe requires caution since, at first, the data for training and validation are, considering the characteristics of the process, typically non-balanced, Heinze et al. [3]. In fact, although stuck pipe occurrence is common, during most part of the operations the phenomenon does not manifest itself.

In a recent study, Elmousalami et al. [2] presents a broad analysis considering twelve machine learning algorithms (single and ensemble ones) applied to the stuck pipe detection. The twelve classifiers include ANNs, random forests, SVMs, decision trees, KNN and others. The results show that the extremely randomized trees model has the best results. In the end, using this method and a genetic algorithm for optimization, the operation parameters (input) are found in order to avoid the stuck pipe occurrence. A similar approach is presented at Toreifi et al. [7].

A relevant aspect about machine learning algorithms applied to drilling operations is the representativeness of the data set. Particularly, for stuck pipe cases, considering that the operations occur for twenty-four hours, a specific sample of attributes may not be representative of such anomaly, which introduces noises into the learning process, Heinze et al. [3]. Alternatively, in a succinct approach and using fewer input parameters (compared to the learning algorithms), Salminen et al. [9] presents a method for calculating the stuck pipe occurrence probability from real-time data, considering two factors: variation rate and deviation of variables in relation to the pre-established model for operations. The method was able to predict cases of stuck pipe, as well as not generating false alarms in the face of normal situations.

Expert systems reveal themselves as an alternative to machine learning algorithms. Okwu et al. [10] presents an extensive revision of the fuzzy logic application at the oil and gas industry, including reservoir evaluation and characterization as well as at drilling and completion operations, including stuck pipe detection. In fact, fuzzy systems aim to reproduce human reasoning and our decision-making ability in the face of scenarios of imprecision and uncertainty, Lin et al. [11]. Naraghi et al. [12] compares the application of ANNs and adaptive neuro fuzzy algorithms to identify cases of stuck pipe, considering as input data operating and drilling fluid parameters. Both methodologies have good accuracy in indicating the probability of stuck pipe occurrence.

The present article proposes an effective and precise alternative for stuck pipe prevention purposes using fuzzy logic. The paper is structured as follow: at chapter 2 the anomaly characteristics and its impacts on the drilling process are presented. Ahead, chapter 3 approaches the main aspects of the fuzzy technique applied at the issue under study, the model building and finally, the data acquisition and treatment. Chapter 4 presents the obtained results through the algorithm application using a real oil well data as the model input. The well is located at Santos basin, brazilian coast. Chapter 5, the last one, summarizes the conclusions of the job.

2 Stuck pipe

This section presents the main characteristics of the anomaly, as well as the main related impacts.

2.1 Phenomenon characterization

Generally speaking, the stuck pipe phenomenon is defined as the sudden suspension of movements of the drill string during operations, Heinze et al. [3]. This imprisonment manifests itself in two main ways: differential sticking (excluded of the scope of this paper) or mechanical sticking. In Salminen et al. [9] studies are presented in which the occurrence of mechanical sticking is found to be higher than those of differential sticking for certain data sets. Whereas the differential sticking is directly affected by the properties of the drilling fluid and well geometry, the mechanical one comes from factors such as: poor well cleaning, collapsing, cuttings generation rate and hydraulic packer ("pack off").

The poor cleaning of the well results from factors such as inefficient fluid for removing the cuttings, or even when the cuttings generation rate is higher than its removal rate. Azeez et al. [13] presents the calculation of the annular speed in order to guarantee efficient cleaning of the well. In fact, the flow of the drilling fluid must be higher than the descending speed of the cuttings, ensuring their removal from the annular space. On the other hand, factors such as insufficient hydrostatic pressure in the annular space of the well and an increase in the cuttings return rate are related to the well collapse.

Finally, regarding the hydraulic packer, regions with a difference in diameter along the drill string, contribute to the deposition of residues in the annular space. In fact, since the diameter of the BHA (Bottom Hole Assembly) is greater than the diameter of the drill pipe stands along the string, the increase in the diameter of the annular space around the drill pipes provides a reduction in the flow speed of the cuttings, increasing their deposition, Fig. 1 (left). For similar reasons, regions known as "rat-hole" also provide a reduction in the speed of the upward flow of the cuttings, potentializing their deposition. Fig. 1 (right).

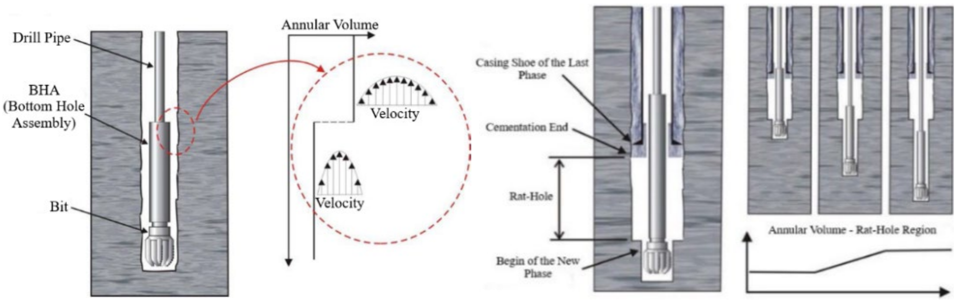

Figure 1. Fluid velocity x cuttings deposition (left side) and annular volume x rat-hole (right side), Ivan et al. [4]

2.2 Impacts due to stuck pipe

The impacts of stuck pipe are widely recognized in works on the subject. Heinze et al. [3] indicates that, once stuck occurred during operations, it is not possible to determine how long this situation will last. Moreover, stuck pipe is a major cause of non-productive time during operations, as well as of increases in the project cost of the wells, Salminen et al. [9]. In fact, in offshore operations, stuck pipe occurrences can increase the cost of developing a well by up to 30%, Toreifi et al. [7].

The drill string prisoning directly causes delays in the construction schedule of the well, given the need to adopt mechanisms for its release. It is worth noting that if the tension to release the drill string to be applied is higher than the maximum stress supported by the drill pipes, it is necessary to adopt special techniques for drill string release, such as the use of drilling fluids with specific characteristics and / or activation of the drilling-jar device, used for this purpose. However, the use of this device is ineffective in some cases, especially in situations where it is positioned below the stuck point, Heinze et al. [3].

It should also be noted that the use of the drilling-jar device requires in many cases, the subsequent inspection of the drilling derrick equipment due to the risk of falling objects due to the efforts experienced by the structure. These factors represent times not initially accounted for in the well construction schedule, potentializing project delays. In addition, this represents an additional fraction of time of contract of the drilling rig daily rate, leading to an increase in the total cost of the well.

In more severe situations, if the contingency actions have no effect, the stuck pipe can lead to complete loss of the drill string and even abandonment of the well, Shadizadeh et al. [8].

3 Fuzzy logic and stuck pipe prevention

This section approaches the fundamental features of the fuzzy logic, its application on the issue under study and the acquisition and data treatment process.

3.1 Fuzzy system for stuck pipe prevention

Fuzzy systems aim to reproduce human reasoning and its ability to make decisions in the face of scenarios of imprecision and uncertainty. As mentioned in Lin et al. [11], like the ANNs, fuzzy logic has the ability to increase the intelligence of systems, working in an inaccurate, uncertain and noisy environment. Indeed, the adoption of a fuzzy system directly captures the perceptions of experts on the subject, from the fuzzyfication process of the variables, to the establishment of the set of rules. In fact, the expert system is opposed to machine learning algorithms since the transmission of information occurs directly and not through the training data set.

Tavares [1] addresses the behavior of the drilling process variables in the face of stuck pipe occurrences. Indeed, the combination of the variables pumping pressure (SPP - Stand Pipe Pressure), load on the hook (WOH - Weight on Hook), torque and drilling rate (ROP - Rate of Penetration) is able to indicate the occurrence of this anomaly. Similarly, Salminen et al. [9] adopts the variables SPP, WOH and torque as input to its model for the purpose of preventing stuck pipe occurrence.

Each of these variables carries a portion of information which contributes to the manifestation of the phenomenon. Namely, obstructions in the annular space due to the accumulation of cuttings causes an increase in pumping pressure. In addition, the sudden wedging of cuttings around the drill string will lead to a peak in WOH ("drag"). About torque, the more congested the annular space due cuttings, the greater the resistance to drill string rotation and therefore the torque. Finally, ROP directly influences the rate of generation of cuttings and, therefore, the state of cleanliness of the well.

Thus, for this work, the system's input variables will be considered, Fig. 2: SPP, WOH, torque and ROP for the purpose of preventing stuck pipe. As an output, the system will provide four diagnostics: normal drilling and alarms between 1, 2 or 3, the latter being more severe in probability of occurrence of stuck pipe.

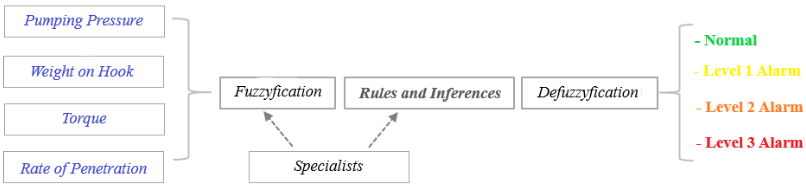

Figure 2. Fuzzy system for stuck pipe prevention

Azeez et al. [13] concludes that the operation team must be attentive to all the signs that the well can provide in order to take actions in a timely manner in order to avoid stuck pipe.

In this context, on the output of the system Fig. 2, the level 1 alarm does not require the operator to act and indicates the process monitoring by the system. However, the level 2 alarm represents primary evidence of stuck and it is recommended that measures be taken, such as better cleaning of the well for example. However, operations can proceed with caution. Finally, the level 3 alarm indicates the imminence of imprisonment of drill string, requiring immediate action by the operator.

For fuzzyfication purposes, considering the input variables, qualitative levels were defined: low, medium and high. In addition, triangular membership functions were used for all variables and levels adopted. For the maximum excursion limits for each variable, the following were considered: the highest values supported by the equipment (SPP), the maker manuals specifications (Torque, WOH) and typical values (ROP).

Next, considering the experts perception of the behavior of process variables in the face of the stuck pipe scenario, the rules of the fuzzy system were established according to Tab. 1. Namely, the objective that permeates the rules of the table is to capture the gradual indicative of the process in relation to stuck pipe, that is, in general, the greater the number of variables at a high level potentiates the occurrence of stuck.

It is noteworthy that for the output variable, intended to indicate the alarm level in relation to the occurrence or not of the anomaly, it was considered an excursion limit 0 - 1, corresponding to the probability (%) of occurrence of the phenomenon. Each alarm level was allocated uniformly (25% for each one), considering the limits established for system output (0-1). That is, an output between 0.25 - 0.50 represents level 1 alarm, 0.50 - 0.75 level 2 and finally, 0.75 - 1 level 3 alarm. Values below 0.25 are considered normal drilling.

Table 1. Summary of the rules fuzzy system

SPP	WOH	Torque	ROP	Alarm level
Low	Low	Low	-	Normal
One variable on "high" and the three ones on "low"				Normal
Two variables on "high" and the two ones on "low"				1
Three variables on" medium"				1
Two variables on "high" and the two ones on "medium"				2
All four ones on "medium"				2
From three variables on "high"				3

That is, considering the information presented and the system structure of Fig. 2, the algorithm works as follows: initially the input variables, at each instant of time, are converted into the fuzzyfication process at high, medium or low levels through the membership functions defined for each input. Once the levels of each variable are established, considering the rules in Tab. 1 and the defuzzyfication process, the algorithm will provide a value between 0 - 100%, corresponding to the probability of occurrence of stuck pipe, which will be classified as normal drilling (0-25%), or alarms levels 1-3. The algorithm was built in Python language.

3.2 Dataset and definitions

Based on daily operations reports, cases of stuck pipe were raised during the construction of an oil well off the Brazilian coast (Santos basin). In addition, data from normal operations (without stuck) was also collected during the same period of time. In this way, 25 samples of data were collected referring to intervals where stuck pipe occurred as well as drilling intervals without drill string prisoning. Of this total, 4 intervals present stuck pipe occurrence. It is worth mentioning that only drilling operations are the scope of this work. The transient ones like drill stand building, filling and string circulation and similar ones are not scope of this paper.

The data samples have the values of the input variables of the system Fig. 2, over time, in addition to the depth of the drill bit, making it possible, together with the information in the operator's report, to identify the exact point of imprisonment for the applicable cases. In order to remove the noise on the input variables, they were initially subjected to a Savitzky-Golay filter, Savitzky et al. [14], with interval size 101 and a polynomial of order 5 to be adjusted.

According to the variation of these two parameters, the filter changes the attenuation of its output. A softer filter preserves the dynamics of the system, but induces a large number of false alarms. On the other hand, a more intense filter provides a smoother signal although it hinders the algorithm to identify the occurrence of stuck pipe. For the parameters chosen here (101, 5) the algorithm was able to perform as expected.

Complementing the information presented on the previous section, the Fig. 3 shows the inputs SPP, WOH and torque few instants before one of the stuck pipe occurrences, indicated by the dashed red line. The red arrows indicate the increasing of the variables close to this point.

Considering the information in Tab. 1, the combination of these three variables at high level, according to the code setting, represents a sufficient condition for the indication of level 3 alarm for the operator. These characteristics will be explored in the next chapter with the results of applying the algorithm to the presented data set.

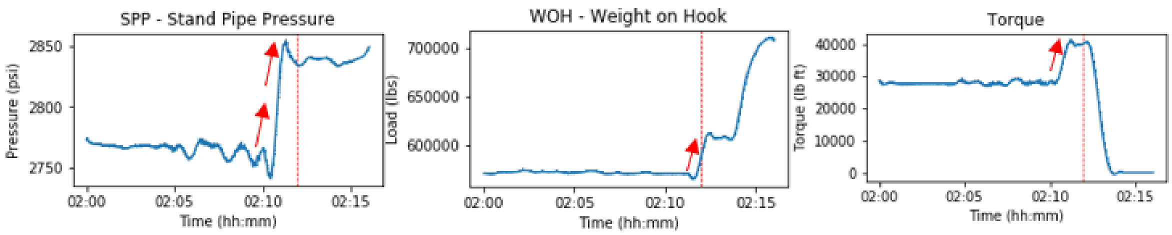

Figure 3. Variables dynamics - stuck pipe occurrence

4 Results and discussions

Initially the algorithm was adjusted through one of the cases of stuck pipe under study. Once adjusted, the expected result of applying the algorithm to the other cases corresponds to level 3 alarm, ie maximum alert, a few moments before the stuck point.

Fig. 4 (on top) shows the code response for the drilling interval whose stuck occurred at 5.182 m depth. The graph on the left represents the drill bit depth versus time and, at the beginning, it is possible to check the depth increase after connecting the drill stand. The red dashed line corresponds to the moment of stuck, being verified by interruption the advance of the drill bit. In addition, this information is confirmed through the operator's report.

The graph on the right shows the alarms provided by the code according to the drill bit advance. Note that several level 2 alarms occurred before the last one, just before the stuck point. In fact, although this alarm does not require the operator to act immediately, its intermittent presence requires caution in the continuity of operations. All of these factors result, at about 02:12h, in the last level 2 alarm which rises to level 3, with the stuck pipe being observed. Similar dynamic is valid for the 5.268 m stuck point shown in the bottom graph, Fig. 4.

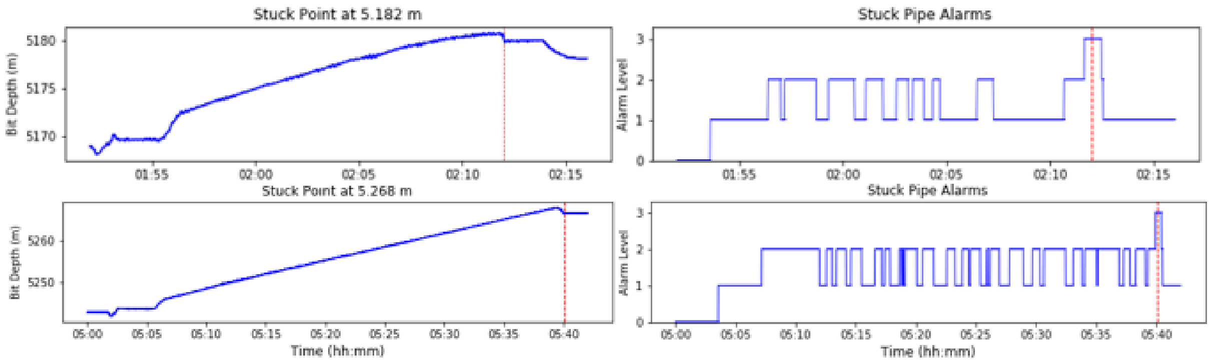

Figure 4. Stuck pipe occurrences and alarms of the fuzzy system

The both previous cases are also presented on the Tab. 2, along with the others corresponding to different depths. The columns "precedency" and "duration" indicate the interval between the first level 3 alarm occurrence and the stuck point, as well as its duration, respectively. It is worth noting that, while the precedency of the alert enhances an effective response from the operator avoiding stuck, its duration reinforces the occurrence of an assertive alarm for drill stand prisoning.

Table 2. Results for stuck pipe prevention

Case	Depth (m)	Precedency (s)	Duration (s)
1	5.049	42	16
2	5.182	15	49
3	5.268	13	30
4	5.502	19	26

In fact, considering that the drilling operations occur under constant monitoring, the level 3 alarms shown in Tab. 2 occur in time enough to take actions such as vertical movement of the drill string or even increasing the mud flow for better cleaning of the well, mitigating the stuck pipe risk. It should also be noted that, like the cases shown in Fig. 4, for other cases of imprisonment, the occurrence of the level 3 alarm is preceded by level 2 alarms, which is a good indication of the potential for stuck that drilling interval.

The non-occurrence of false alarms is critical to the credibility of the code. Thus, as expected, the response of the algorithm for the 21 cases without the occurrence of a stuck pipe did not present any level 3 alarm. The level 1 alarm is the predominant response with minority and isolated level 2 alarms. Regarding the defuzzyfication method, the bisector method presented the best results, meeting the compromise between effective detection of stuck pipe and the absence of false alarms.

In short, the proposed algorithm presented satisfactory results in the face of a substantially unbalanced data set, in view of the predominance of drilling data with intervals without the occurrence of stuck pipe (normal drilling).

5 Conclusions

Machine learning algorithms such as neural networks, and support vector machines have been used to prevent stuck pipe. However, these techniques have limitations, especially in the face of an unbalanced data set.

The use in this work of an algorithm based on fuzzy logic to prevent stuck pipe was able to effectively predict all the cases covered in this paper. In addition, its behavior in situations without anomalies was equally satisfactory. It is also noteworthy that the code was submitted to a set of data that is significantly unbalanced, which reinforces its robustness for this type of situation.

The adoption of real-time analysis techniques, which enhance the operator's performance, with an accurate diagnosis of anomalies, are highly desirable. In effect, the system presented here was able to predict the occurrence of stuck pipe for the cases under study, which would certainly contribute to the continuity and security of operations.

As a future work, the expansion of the model to different wells will be evaluated, allowing its generalization but, nevertheless, preserving its consistency and robustness.

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