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Field Deployment of a LSTM Neural Network Tool for the Rock Formation Consolidation Inference of Brazilian Sandstone Reservoirs

Fabio Rodrigues Gonçalves da Silva and Victor Hugo Ribeiro Carriço, Engineering Simulation and Scientific Software; Alexandre Zacarias Ignácio Pereira and André Leibsohn Martins, Petrobras

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Abstract

The objective of this work is to present a methodology based on the analysis of drilling parameters to infer if a reservoir formation is well consolidated or not, as a support to the selection of sand control strategies.

This work proposes a statistical classification model and the usage of a memory based neural network, known as LSTM (long short-term memory) network. This model explores time series characteristics of the problem and it is validated using a cross strategy. Training performance is evaluated using F1-score, which is a metric that balances precision (percentage of true positives compared to false positives) and recall (percentage of true positives compared to false negatives), chosen because the dataset is unbalanced, there are more samples of one class than the other. The dataset consists of pre-tagged wells, each of them with at least nine hours of drilling data.

Considering 48 cases from different drilled wells, the model was trained to learn how to tag between both patterns. The model analyzes 23 different drilling variables to reach a conclusion.

After training the model, tests were performed and the results showed a high identification efficiency: around 90% of accuracy. That way, mechanical data analysis from the drilling process plays a very important role, supplementing that information and allowing a better understanding of formation behavior by employing what can be considered full-size and a real-time scratch test. Match the collected data with those from wells in which there is logging information, provides geomechanics calibration, and allows consistent rock profiling. It helps to define not only if there is a need for sand control but also the kind of technique to be applied to the analyzed formation accordingly to its consolidation state. The impact of that information is expressive to the completion process.

This feature will be very useful in Brazilian post-salt wells that present sandstone as its reservoir rock formation. Also, as this tool was designed to run in a drilling digital twin, it can be automatically run as soon as the total depth is reached in the drilling phase, providing a fast insight to anticipate completion design.

It is the first time in literature that this approach is used for this specific objective: define if a gravel pack or even any kind of sand control is indeed necessary to be installed based on information gathered while drilling the well. Its great results led this tool to the deployment phase. This work also aims to illustrate the first outcomes of that application in real-time decision-making.

Introduction

In sandstones reservoirs, defining the necessity of sand control is one of the key issues, even in oilfields where operators already have experience with the matter. Cultural bias tends to drive companies to lower optimized patterns, frequently challenged when oil prices decline or when facing economic issues. Unfortunately, most of the time, that reanalysis tends to arrive late or to have limited correlation to current wells due to the absence of specific well logging or core samples to perform mechanical tests. Considering this scenario, mechanical data analysis from the drilling process may provide useful additional information.

The Evolution of sand control strategies in PETROBRAS covers different eras. In the late 80's and in the 90's, the discovery of giant deepwater fields in Campos Basin pushed the development of cost-effective technologies to enhance the attractivity of such projects. The development of Marlim and Albacora fields relied on the construction of hundreds of horizontal injector and producer wells. Due to the non-consolidated nature of the sandstone reservoirs, gravel packing was considered the safer and cost-effective technology for sand control (Sa et al, 1989, Mathis et al, 1999, Cordeiro et al, 1999).

Later, Marlim Sul, Roncador and Albacora Leste brought new challenges associated to the ultra deep waters, fractures and other geomechanical complexities delivering a narrow operational window which restricted the complete packing of annular sections. Different technological solutions were proposed to overcome such challenges (Vosniak et al, 2001, Jardim Neto et al, 2011, Magalhães et al, 2008), all supported by physically based design tool (Martins et al, 2003).

After that, the heavy oils of Espírito Santo and Campos basins required even longer wells and new solutions were provided (Martins et al, 2009, Colbert et al, 2017, Jardim et al, 2012) resulting in a long and well succeeded trajectory of hundreds of gravel packed open hole horizontals (Marques et al, 2007, Marques and Pedroso, 2011, Pedroso et al, 2015).

Due to economical constraints, several authors presented studies questioning the real necessity of gravel packing 100% of the wells in a new project (Cunha et al, 2014, Ferreira et al, 2009). The present study tackles in the same point considering a new perspective: consolidation inference based on data analysis.

Methodology

This topic describes technical developments on using drilling information gathered by a real-time monitoring software, or drilling digital twin (Gandelman et al., 2013), to determine formation consolidation.

Real-time drilling data is an essential tool to increase performance and operational safety, especially when operating in challenging environments. In this scenario, it is highly attractive to use new tools that can anticipate possible risks to the operation, aiding in decision making in order to guarantee operational efficiency and safety.

The data for each well consists of 23 engineering variables (standpipe pressure, block position, fluid flow, ECD, bottom WOB, hook load, bottom torque, annulus pressure, etc), monitored and collected by the drilling digital twin; and geology data, manually provided. Due to discrepancies of availability of geology data for some wells, two LSTM (Hochreiter and Schmidhuber, 1997) models were created, the first using only the engineering variables and the second using both data. This section explains the processes used on the data science/mining, development and on the model creation.

Data Science/Mining Process.

Based heavily on CRISP-DM process methodology for data science/data mining applications, this process iterates over the steps of this cycle in a sequential manner, with constant iteration in overlapping steps, as illustrated on Figure 1.

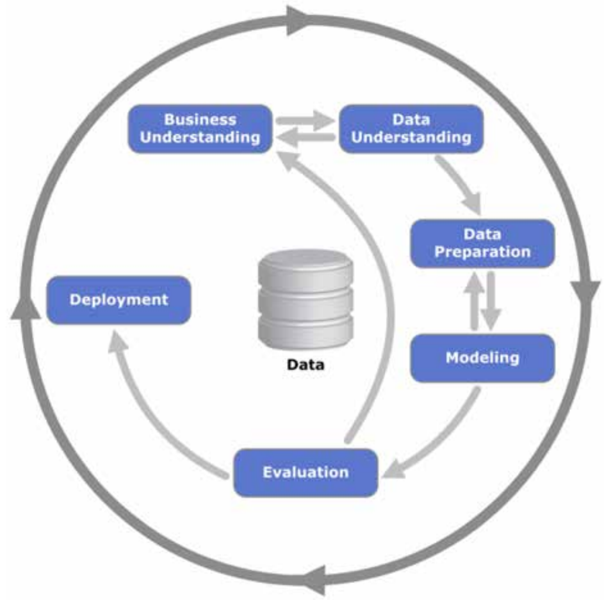

Figure 1—CRISP-DM methodology cycle for data science projects.

Although meant to be used as a continuous cycle procedure, it's often necessary to go back to previous stages in development to retrace business and data-based decisions to allow a concise development in further stages. There is a clear trade-off between the time spent improving the project before its evaluation and deployment and the quick validation of that project. This is important so we don't overextend our efforts in data preparation or modeling stages when key decisions in business or data understanding need to be revisited and refactored.

Domain experts and other specialists were consulted in the business and data understanding phases, where we traced the formal objective of the endeavor, as well as listed the available data sources and formats.

Development.

Engineering data is gathered on steps of 10 seconds, creating a time series for each variable. The timesteps in which bit depth and hole section data are different were removed from analysis. The idea was to analyze only drilling time when the drill bit was touching well bottom. This iniciative, aimed to increase data significance, is shown on Figure 2:

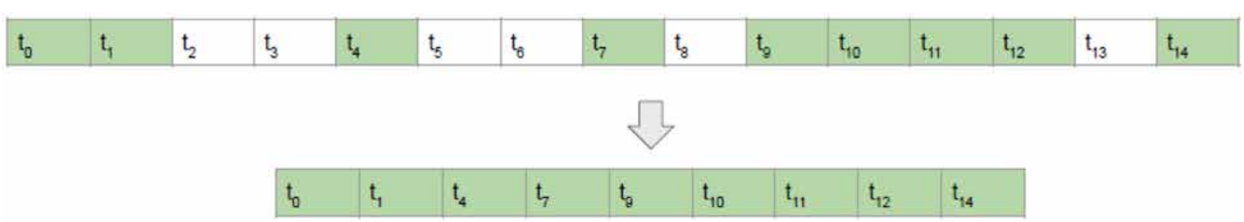

Figure 2—Custom filtering applied to time series.

It creates breaks/discontinuities in the original sequential form of the time series. These discontinuities can cause problems in the dynamic analysis of events, but since this is based on a static analysis of dynamic data, it should be enough to trace early conclusions, starting with simplification and increasing complexity as we go.

The filtered values are kept in the same order, configuring a new sequential time series, where detailed resolution of the events is lost but overall behavior should be preserved. That is a hypothesis that had to be proved by fitting the model to this data.

The aforementioned filter and all other data manipulation is made with Pandas (McKinney, 2010), a python library for Data Analysis.

Historic data from 36 wells were gathered for training. Data from cases with the same hole section were concatenated, and different hole sections were treated as different datasets, this way augmenting training data from 36 to 48 datasets.

Using supervised learning, the objective was to classify each drilling window on consolidated or unconsolidated classes, so prior knowledge of this classification is needed for training and test data.

Model Creation.

The topology chosen for both models was a single LSTM hidden layer, a standard SoftMax (Goodfellow et al., 2016) output layer for binary classification, and an input layer that receives a window of one hour. From each case, 9 windows of one hour of drilling were used for training.

Since the development environment for the drilling digital twin uses python, the tech stack was chosen to work in this language. Tensorflow (Abadi et al., 2015) was selected as the platform for the implementation of this machine learning algorithm, with the Keras (Chollet et al., 2015) application programming interface, which helps handling training algorithms, and Scikit-Learn (Pedregosa et al., 2011), to make performance analysis. Out of the multiple training runs executed, the highest average f1-score on the training set was selected. This metric was chosen because it is similar to accuracy but gives equal weight to precision and recall (Sasaki, 2007).

Two different models were created:

- Model #1: takes into consideration only engineering real-time data;
- Model #2: considers engineering and geology data.

Models are also able to infer the precision on their response. Basically, when the data analysis models are analyzing the whole reservoir drilling dataset, they will provide the amount of time that it matched the "consolidated" and the "not consolidated" tags. For example, if a specific reservoir is tagged as consolidated with a 72% precision, it means that 72% of the analyzed dataset matches what this model learnt as consolidated, and 28% as unconsolidated. As precision gets close to 50%, it can be inferred that this rock formation is partially consolidated.

Results

Results are here presented based on the classification task, which is to predict whether a well/hole section or window is consolidated or not. Translating this to algorithmic language for binary classification, whether the output is 0 (unconsolidated) or 1 (consolidated).

There are several classification metrics that allow us to understand the performance of a classification model. ROC (Receiver Operating Characteristic), illustrated on Figure 3, was chosen due to its explanation capability, both visually and theoretically, for experts in the field and newcomers alike.

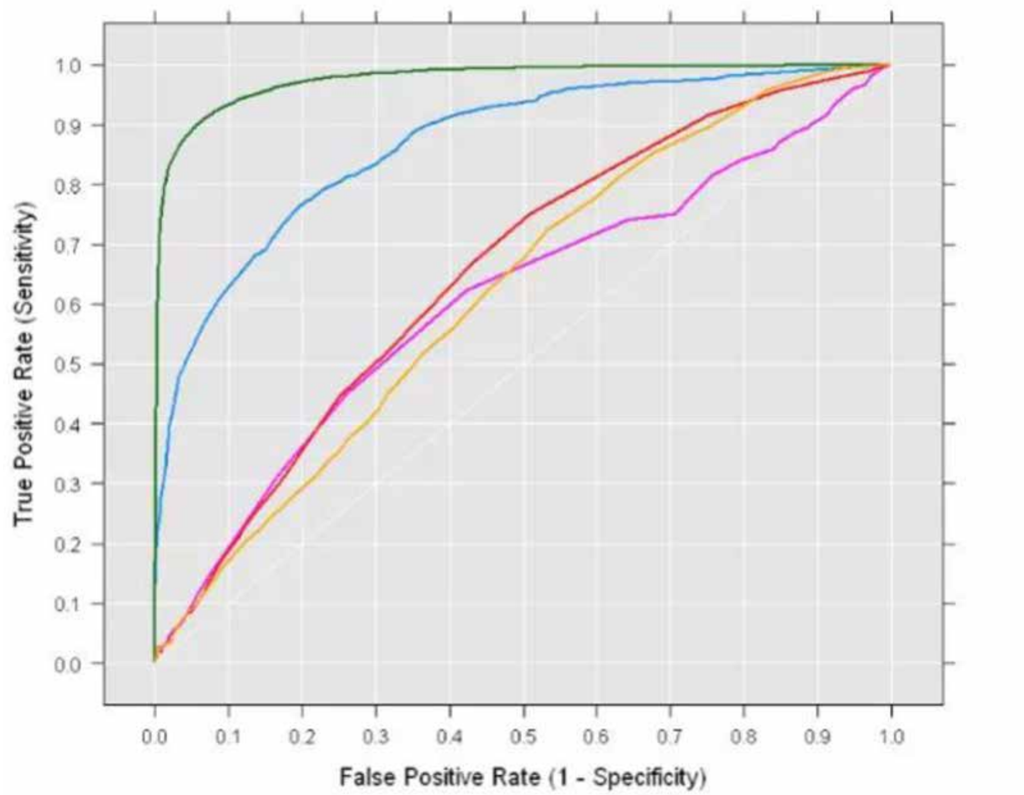

Figure 3—Sample ROC curve of a classification task.

The ROC curve has been widely used in medicine, natural hazards and engineering, and shows the diagnostic ability of binary classifications. The curve is constructed by plotting the TPR (True Positive Rate) against the FPR (False Positive Rate). TPR is the proportion of observations that were correctly predicted positive out of all positive observations. FPR is the proportion of observations that were incorrectly predicted to be positive out of all positive observations. This approach is based on supervised learning, where all samples have a target, whether or not the model knows about it, it'll be evaluated based on its inference.

The ideal classifier should then have the least amount of FPR while obtaining the most amount of TPR, this means that the closer it is to the upper left corner, the better. To summarize this into one metric we use the AUC (Area Under the Curve), which is the integral of the present domain, having its value from 0 (random decision) to 1 (ideal classifier).

Present Work Results.

From the 48 analyzed cases (different well datasets), 37 were used to train the models on how to tag a reservoir rock formation (consolidated or not), and 11 were to test their performance. After analyzing 23 different engineering variables and geological data from each dataset, the models reached around 90% of accuracy.

Figure 4 illustrates through ROC curve that consolidation inference model presented a high discretization indicating high number of test samples and high representativeness.

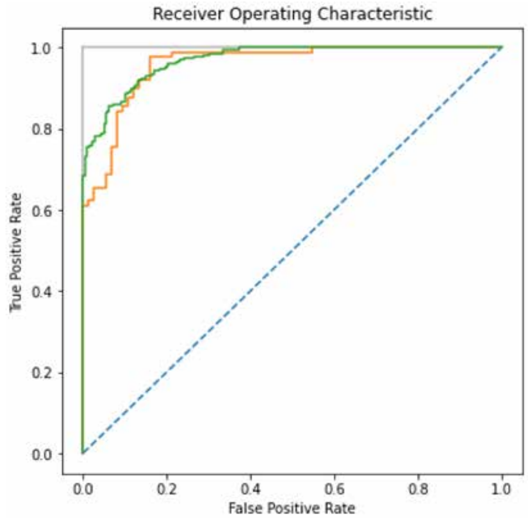

Figure 4—ROC curve obtained for this work. Green line shows training data and orange line shows test data ROC curves, respectively.

Final Validation.

As a final validation step, 17 new datasets were chosen between pre-salt and post-salt recent wells, from 2021 and 2022. This topic will present the obtained results for the two different models:

- Model #1: takes into consideration only engineering real-time data;
- Model #2: considers engineering and geology data.

First, it was used Model #1 to test if it could match the geologists tagging for the wells that present consolidated reservoir rock formations. Table 1 illustrates the obtained results as follows:

Table 1—Rock formation consolidation inference accuracy for the consolidated reservoirs using Model #1.

Datasets		Model #1	
Geologists Tagging	Wells	Model matched?	Precision
Consolidated Rock Formations	Well #1	Yes	72%
	Well #2	Yes	100%
	Well #3	Yes	92%
	Well #4	Yes	100%
	Well #5	Yes	100%
	Well #6	Yes	81%
	Well #7	Yes	100%
	Well #8	Yes	100%
	Well #9	Yes	56%
	Well #10	Yes	100%
	Well #11	Yes	61%
Average Accuracy		100.00%	

Then, still using Model #1, it was verified if it could match the geologists tagging for the not consolidated wells. Table 2 illustrates the obtained results:

Table 2—Rock formation consolidation inference accuracy for the not consolidated reservoirs using Model #1.

Datasets		Model #1	
Geologists Tagging	Wells	Model matched?	Precision
Not consolidated Rock Formations	Well #12	Yes	80%
	Well #13	Yes	96%
	Well #14	Yes	92%
	Well #15	Yes	91%
	Well #16	Yes	97%
	Well #17	Yes	96%
Average Accuracy		100.00%	

After that, joining geology data by using Model #2, it was tested if it also could match the geologists tagging for the consolidated cases. Table 3 illustrates it:

Table 3—Rock formation consolidation inference accuracy for the consolidated reservoirs using Model #2.

Datasets		Model #2	
Geologists Tagging	Wells	Model matched ?	Precision
Consolidated Rock Formations	Well #1	Yes	82%
	Well #2	Yes	100%
	Well #3	Yes	100%
	Well #4	Yes	99%
	Well #5	Yes	96%
	Well #6	Yes	100%
	Well #7	N/A	
	Well #8	No	83%
	Well #9	Yes	100%
	Well #10	N/A	
	Well #11	Yes	96%
Average Accuracy		88.89%	

For Well #7 and Well #10, geology data was not available.

Finally, with Model #2, it was tested if it also could match the geologists tagging for the not consolidated cases. Table 4 illustrates its results:

Table 4—Rock formation consolidation inference accuracy for the not consolidated reservoirs using Model #2.

Datasets		Model #2	
Geologists Tagging	Wells	Model matched ?	Precision
Not consolidated Rock Formations	Well #12	No	100%
	Well #13	Yes	96%
	Well #14	N/A	
	Well #15	Yes	91%
	Well #16	Yes	99%
	Well #17	N/A	
Average Accuracy		75.00%	

For Well #14 and Well #17, geology data was not available.

It can be observed that both models reached great results, especially for the simpler one, which analyzes only engineering data. This model got 100% of accuracy on the final validation test, matching all tagging performed by the most senior geologists in the company.

Field Integration

After obtaining great results by training and testing models with 65 cases (37 cases – training; 11 cases – tests; 17 cases – final validation), this tool was moved recently to the deployment phase. This section presents the first outcomes of that application in real-time decision-making.

Marlim.

A well that was drilled in Marlim field up to the beginning of October/2022 presented the use of OHGP (open hole gravel packing) on its completion plan as the specialists understood its reservoir sandstone as unconsolidated. Then, for the first time, Model #1 was run to verify if this conclusion was correct, as Figure 5 illustrates below:

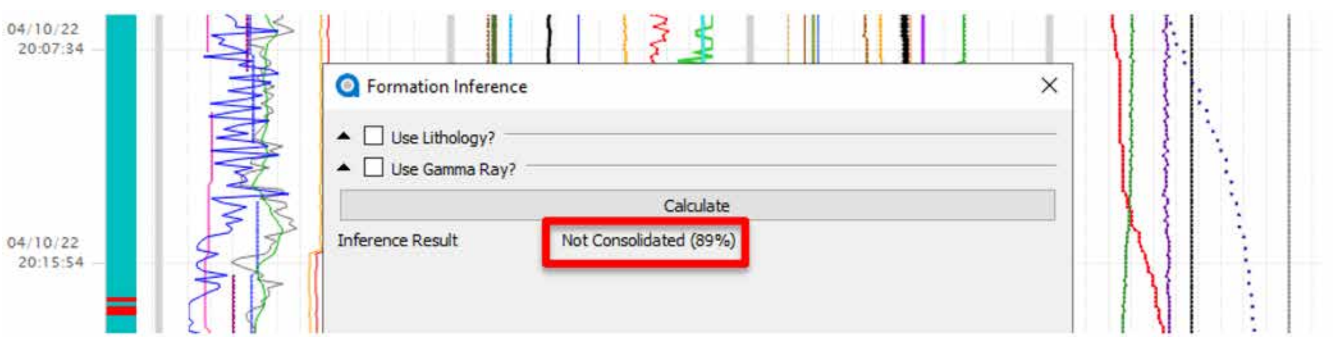

Figure 5—Real-time rock formation consolidation inference for a recent Marlim well.

Model #1 inferred that reservoir drilling dataset presented a not consolidated state in 89% of its entire range. Its result reinforced specialist opinion and OHGP was run as predicted to be.

Final Remarks

This tool was designed to run as a module of a drilling digital twin (Gandelman et al., 2013), and can automatically deliver consolidation analysis as soon as the total depth is reached. The current way to perform this kind of analysis depends on tripping drill string out of hole to collect all needed data. So, with the real-time data analysis model, it is possible to run complete models quick enough to provide insights and to optimize completion design.

The idea is to use this tool before the completion phase. If a sandstone is consolidated, a gravel previously scheduled to be used may not be displaced. So, this validated module flexibilizes the conservative idea of always using gravel packing strategies in Brazilian post-salt wells (exploratory or development wells) that present sandstone as its reservoir rock formation.

Besides, this information can provide the basis to extend fast completion techniques application, such as true one trip configurations, to a larger number of wells, saving up to 15 days of rig time and correspondent tens of millions of dollars per well.

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