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Oil Leak and Seawater Influx Through Partial Ruptures in Subsea Petroleum Production Pipelines

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Abstract
Leak detection in pipelines for subsea oil and gas gathering systems is a relatively new subject to the industry and not many bibliographic resources are available. Petrobras offshore production facilities comprise thousands of kilometers of subsea pipelines for collecting the multiphase production of wells, which makes them a relevant scenario for building a framework for leak detection. For this reason, during the last years a huge effort has been put into building a fast and reliable detection framework of possible leaks occurring from the subsea tree up to the platform. A software-based leak detection system was created and the relevant infrastructure was updated to allow for the permanent monitoring of the subsea flowlines of about 100 wells. The system relies on process variables and on a machine learning algorithm trained to interpret the field data and indicate the suspicious events. Tests of the algorithm over the database points to an accuracy ranging from 87 to 97%.

Keywords
Leak detection, influx, Pipeline

Introduction
Fast and efficient leak detection in subsea production pipelines and equipment has long been a challenge for the oil industry. However, it has recently become even more important as regulatory and environmental pressures increase. The purpose of a leak detection system is a timely identification of pipeline or equipment rupture or perforation. Depending on specificities, such an event may promote oil and gas leakage or sea water influx. In Petrobras' offshore scenario, this matter acquired importance for most of the oil production comes from subsea completions and many tiebacks rely on flexible pipelines, which are subject to degradation in presence of high CO_2 content [1]. For this reason, an effort has been been made during the last four years to build a subsea leak detection system (SSLDS).
A rupture can be total or partial. A total rupture completely separates the pipeline in two ends and all well flowrate is diverted to the ocean (or water could be injected in the well, depending on the pressure at the rupture point). Whereas extremely harmful, this occurrence can be detected by very simple techniques, like low pressure differential at the production choke at the topsides. On the other hand, a partial rupture does not separate the pipeline in two ends and the well maintains connection with the platform. The detection of the latter event is harder than the former, mainly because oil and gas keep flowing to the platform, tough at a lower flowrate. Moreover, the lower the leakage or influx, the harder will be to detect the accident.
In this work, a technique based on machine learning for detecting partial ruptures is presented. The system was designed to comply with the local subsea architecture, where only pressure and temperature online data are available but no flowrate measurement. After that, operational metrics involving leak detection are shown and discussed.

Methodology

Data Generation
The approach adopted for the present SSLDS relies on the similarity between an anomaly, i.e., a purported rupture, and a vast collection of leakage and influx data previously catalogued. For being a rare occurrence, process data related to ruptures in multiphase subsea pipelines is normally not available. Due to this lack of data, training a SSLDS becomes a great challenge.
The solution to this problem was to generate artificial data of subsea pipeline ruptures with transient multiphase flow simulations, for which the code OLGA (version 7.3.3) was selected.
At first, a collection of simulation models of Petrobras' oil production wells was selected. A pressure source was added to the pipeline of each model and triggered after a specified simulation time. This pressure source was set with a pressure equal to the hydrostatic pressure at the seabed

position. Water was injected inside the line if the hydrostatic pressure was greater than the flowline pressure; otherwise, the production fluid (oil, gas and water) was diverted to the source.
For each model, multiple simulations were executed with a set of randomly chosen parameters within a given range. The selected parameters were rupture diameter, rupture position, well productivity index, reservoir pressure, water cut, gas-oil ratio and production choke opening.
The last step was removing simulations with numerical problems and physically implausible values. After that, a dataset containing time series from different variables and positions was obtained. The most important variables for the subsequent analysis were pressure and temperature at the Subsea Tree and upstream the production choke, which are the points where field instruments (sensors, for short) are usually available. This results in a huge database comprising a variety of cases with leakages, influxes and periods or normal operation. The time series from these four sensors were used as input in the machine learning task. The oil, gas and water flowrates through the rupture were collected and used to determine if a leak or a water influx had happened in each case.

Feature Extraction and Training Algorithm

The classifier, which is the function derived from the training process, was developed using an approach to compare the steady states before and after the rupture. The following feature was extracted from each time series:

$$x_{feature} = \frac{x_{final} - x_{initial}}{x_{initial}} \qquad (1)$$

where $x_{feature}$ is the calculated feature, $x_{initial}$ is the variable's steady state value before the event and x_{final} is the steady state value after the event. During the model's development, feature extraction and classifier training, the simulated steady state values were adopted for $x_{initial}$ and x_{final}. However, during the operation, the evaluation metrics consider moving averages for $x_{initial}$ and x_{final}. The former is calculated within a six-hour window, being the first four hours for the effective average and the last two simply an offset; and the latter is carried on a 30-minute window. These moving averages are consistent with the ones implemented in the deployed model.
This feature extraction was applied to the following measurements: pressure at the wellhead, temperature at the wellhead, pressure at the production choke upstream and temperature at the production choke upstream.
Figure 1 shows every possible two-dimensional scatterplot with the calculated features of the four sensors. An analysis of this graph reveals that leaks and water influxes present very distinct behaviors, which reinforces that each event should be treated by a different classifier.

Finally, SVM – Support Vector Machine [2] – using a gaussian kernel function was the chosen machine learning algorithm for classification and testing task. With this method applied to the four-dimensional input data, some points are chosen as kernels and a 4D-region is derived from that. The classifier labels any sample point as a possible leak (or water influx) if this point is inside the 4D-region formed by the kernels.

Results and Discussion

This classifier was trained and validated using the features shown in preceding section. But the test was done with the raw time series of measurements.

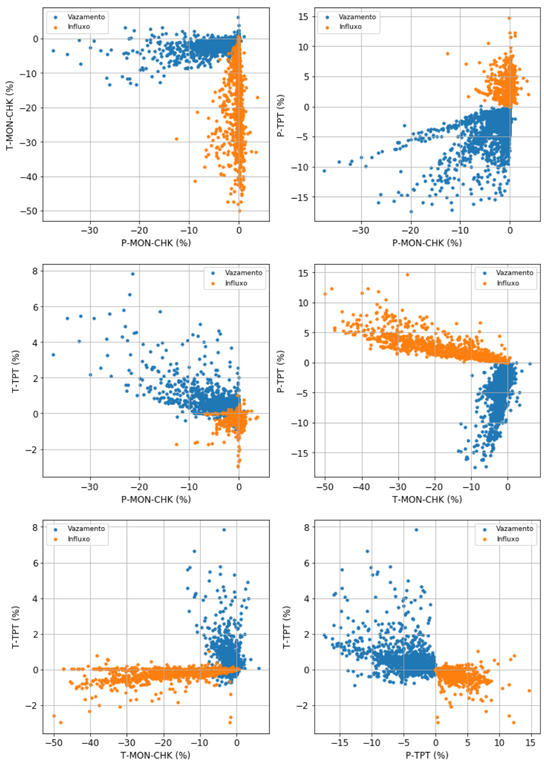

Figure 1. Sensor Variation from the leak and water influx simulations

This was applied to each sensor and each time instant, and leak and water influx probability was returned by the classifiers. Finally, random noise was added to the test data to let the simulated date closer to real cases. Figure 2 shows an example done in a single leak simulation data. In this case, the leak classifier successfully detected the event a few minutes after the rupture. The water influx classifier also didn't change its input.

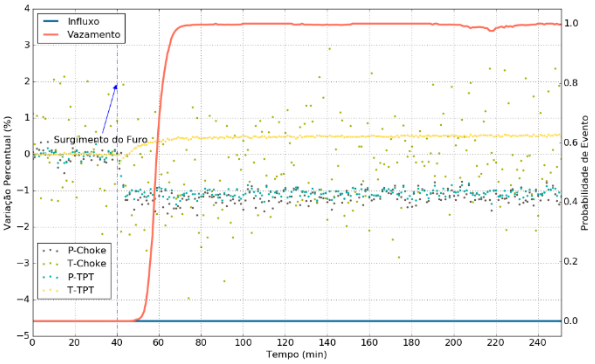

Figure 2. - Leak Test Case.

In the test dataset, the leakage and the seawater influx classifiers obtained accuracy of 86,9% and 97,2%, respectively.

The classifier was deployed embedded in Petrobras' Intelligent Production Surveillance System, an event detection system such as [3], monitoring the possibility of partial ruptures in production pipelines from 100 oil wells, connected to 16 floating production units. The alarms are monitored 24 hours a day by onshore teams. 9 of these production units, encompassing 55 oil wells, also rely on an automated system which can shut down the subsea valves in case of leakage or seawater influx detection.

On average, the system coverage is around 60% of the time, due to a few limitations, such as its inability to accurately classify a partial leakage during transients. Historically, only less than 2 unintended alarms (false positives) per production unit are announced per month on average, a factor that leverages the operators' trust in the system. To the present date, no partial rupture was observed during operation within the set of production wells exposed to CO_2 stress cracking risk, therefore there are no true positive and false negative alarms statistics.

Conclusions

Petrobras' partial rupture detection system for oil production pipelines was successfully developed and deployed, and since the beginning of its operation has gained crescent notoriety and support along the operational and technical teams. The system's stability and its low false alarm rate, combined with a reliable development methodology, are key points to its acceptance, increasing the probability of successful detection in a real event, mitigating the inherent risk of the operation.

References

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