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Sensitivity Analysis of Scale Deposition on Equipment of Oil Wells Plants

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Oil extraction in deep waters implies the drilling of a salt layer, whose thickness ranges from 1000 m to 2000 m. Unscheduled shutdowns with interruption of production can result from the deposition of lime scale, which can block valves, tubing and flowlines of the oil wells plants. Thus, the prediction of lime scale is fundamental in order to control the performance of valves and actuators, which are expected to operate for a certain period of time under required operating conditions. To this purpose, laboratory tests have been conducted on different materials (25-Cr, 13-Cr, In718, WC) used in off-shore drilling in order to study lime scale deposition under controlled environmental and working conditions (Moura et al., 2011). The data collected in these tests are analysed in this work, to study the influence of the experiment inputs (e.g., material, roughness, sample initial weight, test temperature, etc.) on the outputs (i.e, rate of scale deposition and lime scale final weight and thickness). The idea is to identify the inputs which have the greatest influence on lime scale thickness variations to eventually use them to build an empirical model of the degradation of the oil wells valves and actuators. A sensitivity analysis is performed by resorting to a classification tree, a tree-like graph in which each laboratory test occupies one of the leaves of the tree. The key point of the method is the choice of the selection rules to classify the data. The input variances in the subclasses which are generated at every branching step provide useful information about the most significant inputs. Results are confirmed by different correlation coefficients (Linear, Spearman Rank Order and Kendall's Tau).

1. Introduction

In the last decades, World's oil demand has been continuously increasing. According to the International Energy Agency (IEA), the oil product consumption has increased of about 60 % from 1972 to 2008. To satisfy the demand, exploration has to be continuously augmented, also in deep waters. In 2007, the limit concerning the depth of exploration has reached 7000 m, by the Brazilian company Petróleo Brasileiro S.A. (Petrobras). Such a depth implies the drilling of a salt layer, whose thickness ranges from 1000 m to 2000 m. This salt layer causes the formation of lime scale on the materials of the components of the oil plant, such as valves and actuators; this deposition need to be predicted in order to control the performance of components over the period of time and operating conditions of interest. In fact, this deposition can lead to unscheduled shutdowns with interruption of production and economical losses (El-Hattab, 1985; Moura et al., 2011; Peixoto et al., 2011). Laboratory tests have been performed in order to investigate the effects on the scale build-up, of the new operational

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conditions (i.e., temperature, pressure, brine composition, etc.) found in new exploration activities in deep waters. The objective is to provide useful information for the equipment design and maintenance planning. To this purpose, sensitivity analysis techniques (Saltelli et al., 2000) can be performed to identify the parameters most influent in the scale deposition process. Different approaches exist, based on different mathematical interpretations. In this paper, we propose an approach for sensitivity analysis based on a classification tree (Russel and Norvig, 2003) which allows: i) ranking the importance of the inputs with respect to their influence on the output ii) identifying those inputs which are not relevant for the prediction of the scale deposition.
The remaining parts of the paper are organized as follows: in Section 2, a brief introduction regarding the scale deposition problem and the experimental facility is given; Section 3 reports the sensitivity analysis; finally, in Section 4, conclusion and remarks are drawn.

2. Laboratory tests for scale deposition

Laboratory tests have been conducted on different materials (25-Cr, 13-Cr, In718, WC) used in off-shore drilling in order to study lime scale deposition under different environmental and working conditions (Moura et al., 2011). The tests are performed in a reactor, whose scheme is shown in Figure 1. Test samples are put on one of the 17 shelves (locations) in the reactor, with horizontal or vertical orientation. The equipment can also rotate in order to simulate dynamic flow conditions. The total amount of tested samples is 345. The input parameters that are controlled during the experiments are: material, orientation, location, roughness, initial weight [g], test temperature [°C], test pressure [psi], brine concentration [%], test duration [min], velocity of the flow due to stirrer revolution [m/s]. Material, roughness and initial weight are representative of the characteristics of the sample, whereas the other parameters define the test conditions. In particular, some of them (i.e. test temperature, test pressure, brine concentration and test duration) characterize the working environment. It must be pointed out that material, orientation, location and roughness are qualitative variables (labels), whereas the others are quantitative (measurable) and their interval values are listed in Table 1. The output variables recorded at the end of the test are: scale weight [mg], rate of scale deposition [mg/h], scale thickness [cm]. According to expert judgement (Moura et al., 2011), the most meaningful output in the design phase is scale thickness: therefore, we shall focus on this output.

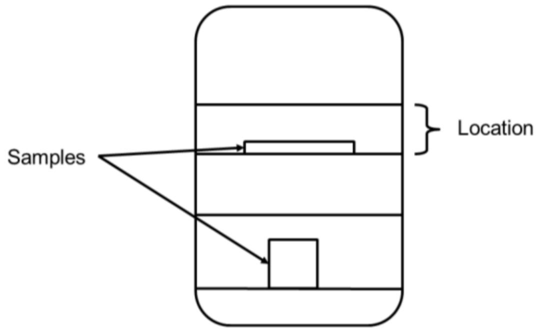

Figure 1: Scheme of the reactor used for tests

Table 1: Maximum and Minimum values of the quantitative variables

Variable	Min	Max
Initial Weight	30.6102 mg	615 mg
Test Temperature	60.9 °C	158.9 °C
Test Pressure	70.3 psia	9830.2 psia
Brine Concentration	50 %	130 %
Test Duration	327 min	22380 min
Stirrer Velocity	0 m/s	0.0283 m/s
Scale Thickness	$2.54 \cdot 10^{-4}$ cm	$6.88 \cdot 10^{-2}$ cm

3. Sensitivity analysis by classification tree

A set of *L* input-output patterns $(\vec{x}, y)$ is available; the input is *N*-dimensional and the output is one-dimensional. The sensitivity analysis method here proposed is based on the development of a classification tree by successive splitting of the *L* available patterns into classes, according to their input values. Each input x_i generates a branching of the tree into two classes: one made of patterns with small values and one with large values. The basic idea behind the method is that if an input greatly affects the output, the two classes built on the basis of its value satisfy the following properties:

- The output values y of the patterns belonging to the same class are similar. This results in a low intra-class variance.
- The output values y of patterns belonging to different classes differ significantly. This results in a large difference between the mean values of the output y in the different classes.

The method entails two steps: i) ranking the input signals according to their impact on the output and ii) quantifying their influence on the output.

Step i) The first step relies on a classification tree (Russel and Norvig, 2003), a tree-like graph where groups of outputs occupy a leaf according to their input patterns. The key point for the development of a classification tree is the choice of the selection rules to classify the data. Let $\vec{x} = \{x_1, ..., x_N\}$ be the input vector containing the N input signals which correspond to the output y. The rules here proposed for the classification tree can be listed as follows:

1. Normalize the input vector elements and the outputs; in particular, let m_i and M_i be respectively the minimum and maximum values of the i-th input signal (or the minimum and maximum values of the output); then, the input x_i (or, in analogous way, the output y) is normalized as:

$$x_i^{norm} = \frac{x_i - m_i}{M_i - m_i} \quad (1)$$

2. Normalized inputs are divided into two classes: large values ($x_i \geq 0.5$) and small values ($x_i \leq 0.5$).
3. For each available input, the difference between average values of the outputs corresponding to the two input classes is calculated.
4. The input which causes the maximum difference between average outputs of large and small input classes is selected as the most significant, and is responsible for the next ramification of the tree.
5. Repeat the procedure until there is a sufficient number of data in the branches.

By so doing, the branching is due to the input which causes the largest difference in the average output value when input values are split into large and small classes (Figure 2).

Step ii) In the second step, the input variances in the two subclasses are used to identify the most important input values. Each branching step originates two output classes, which can be described by the corresponding sample average $\hat{\mu}$ and standard deviation $\hat{\sigma}$. A confidence interval, that is defined as (Montgomery et al., 2011)

$$(\hat{\mu} - \hat{\sigma}, \hat{\mu} + \hat{\sigma}) \quad (2)$$

can be used to verify if the input responsible for the branching is relevant for the determination of the output according to the basic idea of the method. In fact, if the intervals associated to the branching are not excessively overlapping, it means that the considered input is significant because a change in its value (from large class to small class) results in a significant change of the average values of the corresponding output classes and in their effective separation. On the contrary, if the intervals are superimposed, the corresponding change in the output values and the separation of the subclasses are negligible. A scheme of this procedure is presented in Figure 3.

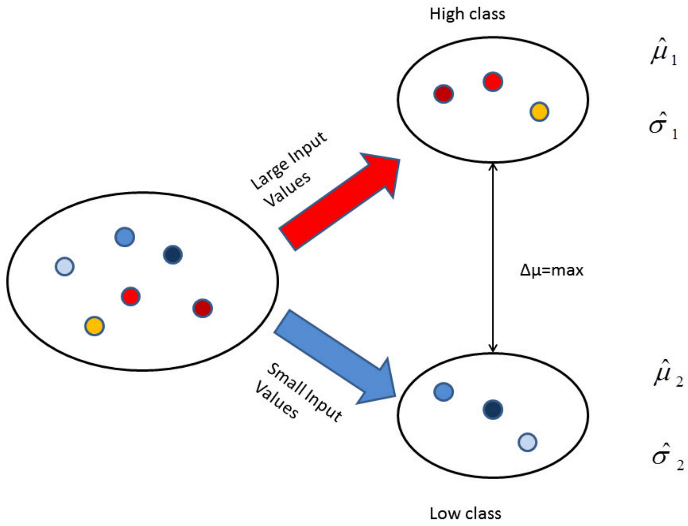

Figure 2. Scheme of the classification rule

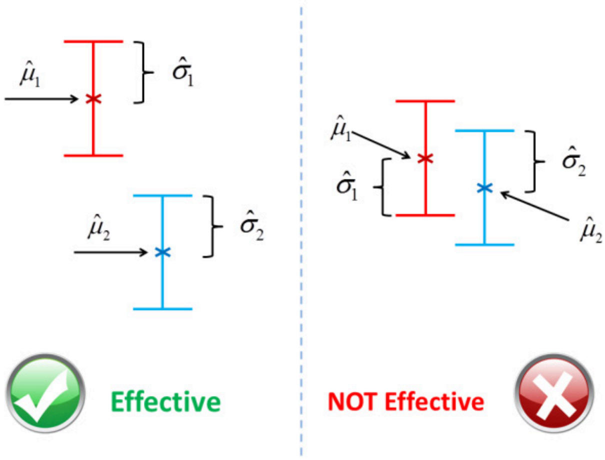

Figure 3. Scheme of the procedure for the detection of relevant inputs

4. Results

For the sake of brevity, but without loss of generality, in what follows we will concentrate on 25-Cr samples only. The total amount of tested samples for this material is equal to 32, a rather small number of examples that challenges the proposed sensitivity analysis approach.

In Figure 4, the classification tree for the experimental data of scale deposition is shown. Every box indicates the input which originates the branching; the branch which corresponds to large input values is marked as "L", while the one corresponding to small values is marked as "S". Following a branch, the sequence of inputs labeling the leaves of the tree provides a ranking of their importance with respect to the impact on the output value. In fact, the input selected for each ramification is the one which causes the highest difference in the average output values of the originated subclasses for that ramification.

In Figure 5, the confidence intervals for the various branches of the tree in Figure 4 are plotted. It can be seen that the first three inputs are the most significant ones because the corresponding confidence intervals do not overlap significantly. Therefore, brine concentration, test pressure and sample orientation can be considered effective in the explanation of the variability of lime scale thickness.

This result has been compared with those provided by three different correlation coefficients: linear correlation coefficient (Edwards, 1976), Kendall's tau (Kendall, 1938) and Spearman rank (Spearman, 1904), whose results are reported in Table 2. Considering that the larger the value of these correlation coefficients, the stronger the dependence of the output on that input, it can be confirmed that the three most significant inputs are brine concentration, test pressure and sample orientation.
In comparison to correlation coefficients, which provide only a measure of the influence of the inputs on the output, this proposed sensitivity analysis technique considers the combined effect of several inputs. Furthermore, from the tree in Figure 6, one can directly obtain the value of the thickness deposition, associated to the corresponding input parameter classes.

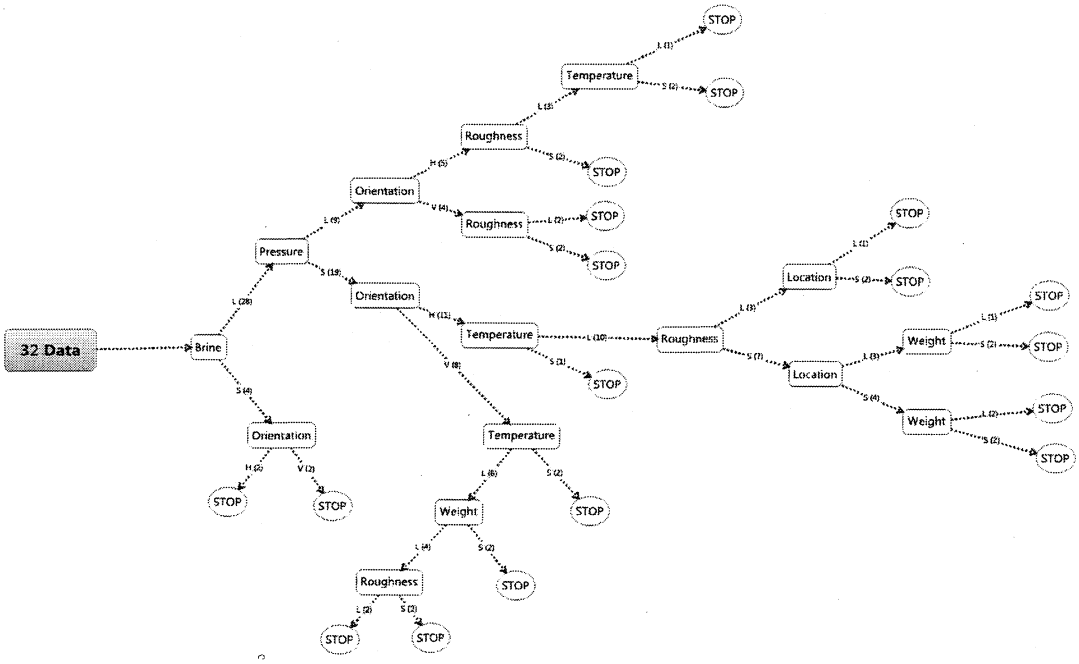

Figure 4. Scheme of the classification rule

Table 2: Correlation coefficients

Variable	Linear	Kendall	Spearman
Orientation	0,4231	0,2546	0,3070
Location	-0,0807	0,0765	0,0895
Roughness	0,1604	0,1245	0,1501
Initial Weight	0,1468	0,0524	0,1180
Temperature	-0,1115	-0,0453	-0,0845
Pressure	0,4201	0,4933	0,6578
Brine	0,4790	0,5155	0,6062

5. Conclusions

In this work, a sensitivity analysis technique has been proposed to identify the most relevant inputs for the determination of the scale deposition in oil well drilling equipment. The method uses a classification tree to rank the influence of each input signal on the output, and a comparison of the confidence intervals of the subclasses corresponding to each branching to evaluate the effectiveness of each input in explaining the output variations.
A comparison between the results obtained by the proposed technique and the ones provided by classical correlation coefficients (Linear, Spearman Rank Order and Kendall's Tau) has been performed, showing the good agreement in the selection of the most significant inputs. Moreover, the proposed technique can give the mean scale thickness for the various input classes identified.

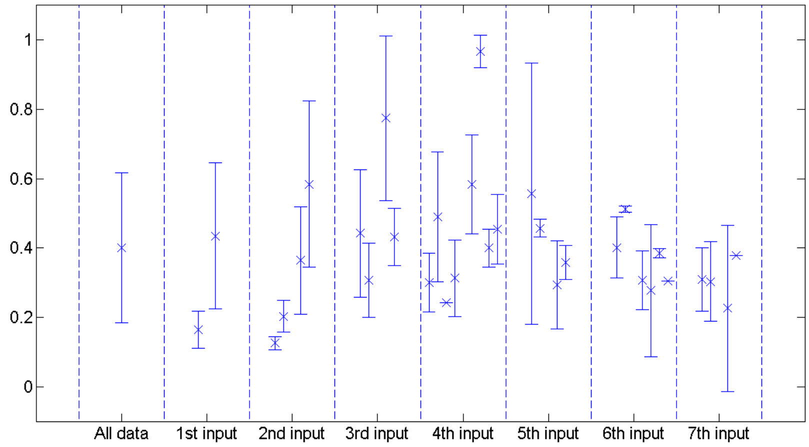

Figure 5. Confidence intervals for the branches of the classification tree

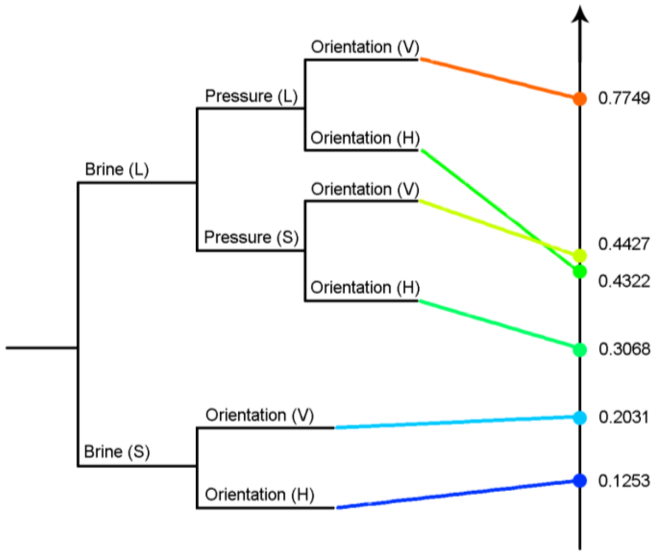

Figure 6. Average output values corresponding to the classes of the most relevant inputs.

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