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Downhole Pressure Estimation Using Committee Machines and Neural Networks

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Abstract: In gas-lifted oil wells the monitoring of downhole pressure plays an important role. However, the permanent downhole gauge (PDG) sensor often fails. Because maintenance or replacement of PDGs is usually unfeasible, soft-sensors are promising alternatives to monitor the downhole pressure in the case of sensor failure. In this paper, a data-driven soft-sensor is implemented to estimate the downhole pressure using committee machines composed by finite impulse response (FIR) neural networks. Experimental results in three real datasets of the same oil well indicate that the identified soft-sensor is able to predict the downhole pressure with satisfactory accuracy. The model input variables were selected by statistical tests which increased insight concerning such variables. Committee machines outperformed single-model soft-sensors on experimental data.

Keywords: downhole pressure, neural networks, ensemble, soft-sensor, sensor failure.

1. INTRODUCTION

The soft-sensors are mathematical models capable of estimating a process variable using measurements of other process variables. They have been used in many industrial applications as process monitoring and sensor fault detection (Fortuna et al., 2007). According to (Kadlec et al., 2009) there are three classes of soft-sensors: model-driven, data-driven and hybrid. The model-driven soft-sensors are based on first-principle models, called white-box models, whilst data-driven soft-sensors are based on models identified using data available from the process, or black-box models. Finally, there are those that incorporate features of these two previous classes, called hybrid soft-sensors.

In the oil industry, one important application of soft-sensors is to estimate the downhole pressure of oil wells, since the monitoring of this pressure allows engineers to optimize production techniques (Eck et al., 1999; Wang and Li, 2013). However, the permanent downhole gauge (PDG) sensor failure often happens (Teixeira et al., 2014). Due to the difficulty in accessing the sensor installation site, soft-sensors are promising alternatives to monitor the downhole pressure when the sensor measurements are no longer available.

Due to their universal approximation capability, Neural Networks models have been widely used to develop soft-sensors (Gonzaga et al., 2009; Roverso, 2009). To improve model performance, *committee machines* can be built (Soares et al., 2011; Sui et al., 2011). The field of committee machines studies the combination of models. As a rule of thumb, combining estimators is more robust and accurate than using a single one (Perrone and Cooper, 1993).

Committee machines can be divided into two groups: *ensemble* and *modular* architectures. The former combines redundant predictors in the sense that each one could solve the task as a whole (Hansen and Salamon, 1990), however, the best result is expected to be achieved by using the combination. In the modular approach, the problem is divided into different sub-tasks and each predictor takes charge of a sub-task whereas the final solution has to be composed of all predictors (Sharkey, 1999).

Thus, the objective of this work is to implement a data-driven soft-sensor to estimate the downhole pressure of a real oil well. The contribution of this paper is to introduce a procedure to select input variables of neural models using statistical tests, and to design *ensembles* composed by Neural Networks models to estimate the downhole pressure. Besides a discussion about some relationships among oil process variables is also presented.

This paper is organized as follows. In Sec. II, a simplified description of the investigated process is presented. The Materials and Methods are presented in Sec. III and Sec. IV presents the results. Conclusions are drawn in Sec. V.

2. PROCESS DESCRIPTION

The offshore oil extraction process involves extracting the oil contained in reservoirs located below the seabed using floating platforms or vessels. These are responsible for

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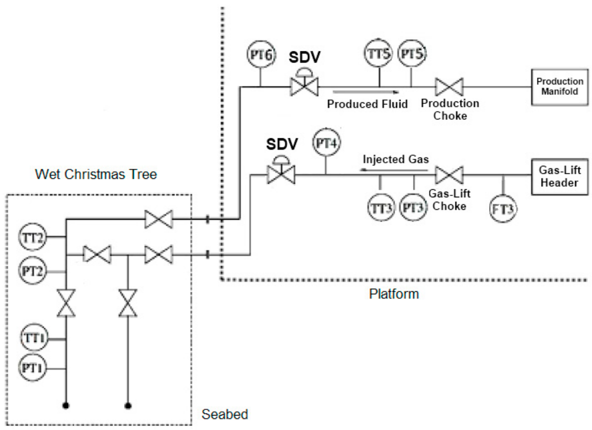

Fig. 1. Simplified P&ID diagram of a gas-lifted oil well. The corresponding variables are described in Tab.1.

Table 1. Process variables. Tags correspond to the codes shown in Fig. 1.

Tag	Process Variable	Location
PT1	Downhole pressure	Seabed
TT1	Downhole temperature	Seabed
PT2	Wet Christmas Tree pressure	Seabed
TT2	Wet Christmas Tree temperature	Seabed
PT3	Pressure downstream of gas-lift choke valve	Platform
TT3	Temperature before gas-lift shutdown valve	Platform
FT3	Instantaneous gas-lift flow rate	Platform
PT4	Pressure upstream of gas-lift shutdown valve	Platform
PT5	Pressure upstream of production choke valve	Platform
TT5	Temperature before production choke valve	Platform
PT6	Pressure upstream of shutdown valve	Platform

the production management, storage and, in some cases, primary processing of the production.

When there are several wells being managed by the same platform, *manifolds are used*. Such pieces of equipment are responsible for the simultaneous production of different wells and may be located at the seabed, and connected to the respective *wet Christmas tree* (WCT). In offshore oil extraction, the *continuous gas-lift method* is usual choice for artificial lift in mature wells (Jadid et al., 2006).

This technique consists of injecting pressurized gas in the production string continuously in a controlled manner. Choke valves located at the platform are used to control the amount of gas. Precise control of the gas-lift operation is necessary, since the ratio of produced oil and injected gas is non-linear, meaning that increasing the gas injection after a point does not correspond to higher production (Ray and Sarker, 2007; Jadid et al., 2006; Singh et al., 2013).

In order to monitor and control the gas-lift system and the oil production, data from several sensors are available to the operator (Fig. 1). One of the available sensors is the PDG sensor (PT1 and TT1), located inside the production string. This location enables the measurement of valuable data for the efficient operation of the production but also renders the sensor subject to intense wear.

Despite improvements in the construction, PDG sensors still have a short lifespan. Approximately 30% of the sensors fail within 5 years of installation (Frota and Destro, 2006). There is, also, a great difficulty or even an impossibility of replacement or maintenance of the sensors due to their location. To perform this tasks, it is usually necessary to stop production, causing major economical losses.

Table 2. Experimental datasets.

Datasets	Size (samples)	Use
A1	55,615	training and validation
A2	95,586	test
A3	41,760	test

Therefore, on the one hand, PDG sensor is a valuable tool to achieve efficient production and, on the other, sensor lifespan is relatively short with replacement or repair being sometimes economically unfeasible. In this context, soft-sensors become alternatives to increase data reliability or even act as a substitute in cases of sensor failure. Thus, this work aims at implementing soft sensors for the downhole pressure (PT1).

3. MATERIAL AND METHODS

3.1 Experimental Data

We will use data from various sensors to identify models to estimate the downhole pressure. In this investigation, the input variables are restricted only to those measured from platform sensors. In a less conservative study variables from the WCT could also be considered.

Three datasets from the oil well A are available. The sampling frequency of these datasets is 1 sample/minute and Tab. 2 summarizes their size and application during the model estimation process. Figure 2 shows the downhole pressure to be estimated for each dataset. Dataset A1 was used to train the neural models and to define their structures (train and validation). Generalization performance was evaluated on the dataset A2 (test). Dataset A3 shows the moment the PDG fails (test).

3.2 Neural Network Models and Committee Machines

In this work, only FIR (Finite Impulse Response) black-box Neural Network (NN) models are identified which can be represented by

$$\begin{aligned} y(k) = F[&u_1(k-1), ..., u_1(k-n_{u1}),\\ &u_2(k-1), ..., u_2(k-n_{u2}),\\ &u_n(k-1), ..., u_n(k-n_{un})], \end{aligned} \qquad (1)$$

where F is a non-linear function implemented by feed-forward multi-layer perceptron neural networks (MLPs), and n_{u_i} is the maximum delay of the input u_i, where $i = 1, \ldots n$ and n is the number of inputs. We choose the FIR structure to prevent obtaining unstable models since the objective is to perform model free run simulation. The model inputs are the following variables measured from oil platform sensors: pressure upstream of the shutdown valve, pressure upstream of the production choke valve, temperature before production choke valve, pressure upstream of the gas-lift shutdown valve, temperature before gas-lift shutdown valve and instantaneous gas-lift flow rate.