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Data-driven soft sensor of downhole pressure for a gas-lift oil well

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ABSTRACT

Downhole pressure is a key variable in the operation of gas-lift oil wells. However, maintaining and replacing downhole sensors is a challenging task. In this context, we design and implement a data-driven soft sensor to estimate online the downhole pressure based on other (seabed and platform) available measurements. Such application is based on a two-step procedure. In the first step, discrete-time black-box and gray-box NARX models are identified offline and independently using historical data. Both polynomial and neural models are obtained. In the second step, recursive predictions of these multiple models are combined with current measured data (of variables other than the downhole pressure) by means of an interacting bank of unscented Kalman filters. In doing so, a closed-loop model prediction is performed. Three issues are investigated in this paper concerning: (i) the usage of a filter bank rather than a single filter approach, (ii) the availability of seabed variables as inputs of the models compared to the case where only platform variables are available, and (iii) the employment of gray-box models in the filters. Experimental results along 7 months of tests indicate that such closed-loop scheme improves estimation accuracy and robustness compared to the free-run model prediction or to the use of a single unscented Kalman filter. The method employed in this paper can also be applied to other soft sensing applications in industry.

1. Introduction

In the last two decades, *soft sensors* have been increasingly applied in process industry as an alternative to traditional hardware instruments. Applications range from oil industry (Domlan, Huang, Xu, & Espejo, 2011; Fujiwara, Kano, & Hasebe, 2012), chemical processes (Gjerkes, Malensek, Sitar, & Golobic, 2011; Jin, Wang, Huang, & Forbes, 2012) to metallurgical industry (Li & Jiang, 2011; Wu, Lei, Cao, & She, 2011), to name a few. Roughly speaking, soft sensors are predictive mathematical models that infer the values of a given process variable from measurements of other process variables (Fortuna, Graziani, Rizzo, & Xibilia, 2007). Though the range of applications covered by soft sensors is broad, their most dominant application field is the *online prediction* of process variables which are measured only at low sampling rates, using expensive or unreliable instruments, or through offline analysis. Other important areas of application include process monitoring and process and sensor fault detection (Kadlec, Gabrys, & Strandt, 2009).

Thus, modeling is the keypoint for soft sensor development. Different modeling approaches may be employed. Two classes of soft sensors can be distinguished, namely, *model-driven* and *data-driven* (Kadlec et al., 2009). The former is based on first-principle models, while the latter uses data-driven back-box or gray-box identified models. First-principle models are generally developed for the planning and design of industry plants and are not recommended for soft sensor development (Kadlec et al., 2009). Also, industrial processes are described by nonlinear phenomena; therefore, nonlinear models should be the natural choice. However, nonlinear modeling is not a trivial task (Aguirre & Letellier, 2009). Alternatively, multiple linear models are often employed in soft sensor applications (Jin et al., 2012; Domlan et al., 2011; Li & Jiang, 2011). Nonlinear black-box models have been increasingly used in soft sensor applications; especially neural networks (Fujiwara et al., 2012; Wu et al., 2011). To the best of our knowledge, gray-box modeling is not often applied to soft sensor development (Sbarbaro, Ascencio, Espinoza, Mujica, & Cortes, 2008). Finally, it is important to point out that soft sensors often employ finite impulse response (FIR) models. Alternatively, infinite impulse response (IIR) models can be combined with FIR models by means of state estimators, resulting in a *closed-loop prediction scheme*; see Fig. 1.

Gas-lift is a technology to produce oil and gas from low pressure oil wells. The gas-lift flow rate is determinant in the well productivity and affects the flow dynamic stability. Also, its value strongly depends on the downhole pressure, which, therefore, must be monitored. According to Nygaard, Naevdal, and Mylvaganam (2006), downhole pressure is the most important variable to describe the dynamics of a oil well. However, maintaining and replacing permanent downhole gauge (PDG) sensors is a challenging task,

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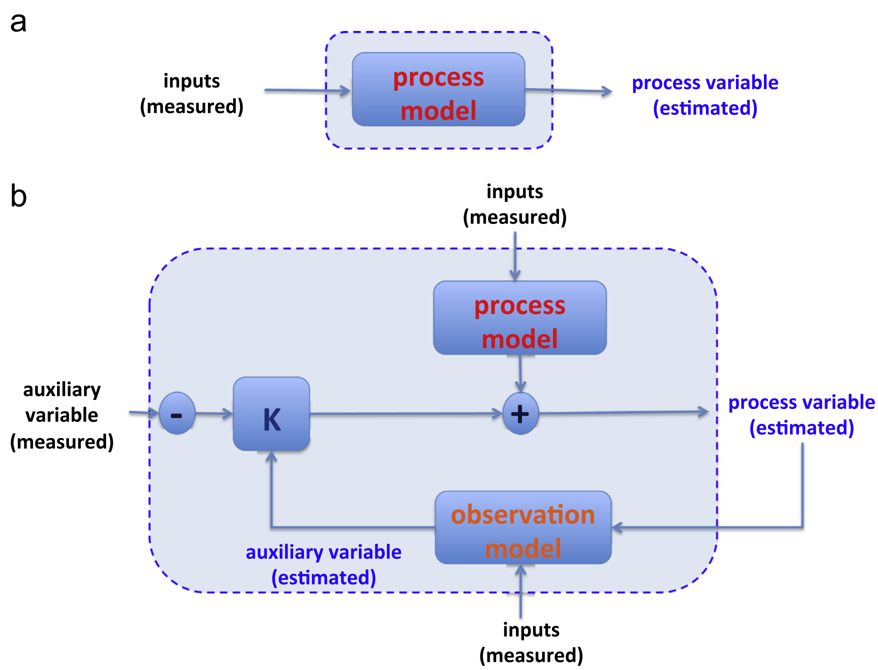

Fig. 1. Comparative perspective of soft sensors concerning modeling approaches. In (a), predictive FIR models yield open-loop estimates while, in (b), the combination of predictive FIR models with measurements of auxiliary variables and observation models by means of a state estimator works as a closed-loop estimation scheme.

especially in deepwater oil wells (Eck et al., 1999). Also, sensor premature failure often happens. Actually, if at all available, downhole measurements are generally unreliable (Aamo, Eikrem, Siahaan, & Foss, 2004). In this context, soft-sensor techniques are promising alternatives to monitor the downhole variables.

In Aamo et al. (2004), Nazari, Mostafavi, and Hareland (2009), Nygaard et al. (2006), Bloemen, Belfroid, Sturm, and Verhelst (2006), model-driven soft sensors are investigated to monitor downhole variables in gas-lifted oil wells. However, a natural shortcoming arises in such cases, related to the need of obtaining physical parameters of the corresponding mass-balance-based nonlinear models. Such issue can be circumvented by employing a bank of locally linear models, for which it is easier to estimate the parameters. Jahanshahi, Salahshoor, and Sahraie (2008) investigate the fuzzy combination of local linear models from simulated data. In all aforementioned applications of soft sensing techniques to gas-lift oil wells, closed-loop prediction schemes are used. Except for Nazari et al. (2009), in all cases above, the extended Kalman filter is used to assimilate measurements of other variables to the predictions of the IIR first-principle models.

In this paper, we employ a two-step procedure to estimate online the downhole pressure of an actual deepwater gas-lift oil well. Indeed, our approach can be applied to other soft sensing problems. Our procedure characterizes a data-driven soft sensor. First, discrete-time nonlinear autoregressive with exogenous inputs (NARX) polynomial models and multilayer perceptron (MLP) neural networks are identified offline using experimental data as in Aguirre, Teixeira, and Tôrres (2005). Two kinds of models are obtained: IIR process models and FIR/IIR observation models. Different configurations of inputs and outputs and of model structures are tested. Each model is built completely independent from the others. Second, an interacting multiple model (IMM) filter bank (Mazor, Averbuch, Bar-Shalom, & Dayan, 1998; Bar-Shalom, Li, & Kirubarajan, 2001) is employed, with each unscented Kalman filter (UKF) (Julier & Uhlmann, 2004) of the bank combining a different pair of process and observation models. That is, local nonlinear "closed-loop" models are combined to yield improved downhole pressure estimates compared to the free-run simulation of a single (open-loop) model or a single UKF. Note that, in our approach, the downhole pressure is assumed to be known only during the system identification step. For practical applications, this is the case after downhole sensor installation, when such sensors are more reliable (Eck et al., 1999).

We therefore investigate three relevant issues regarding closed-loop data-driven soft sensing. First, we evaluate what is the gain of using a filter bank rather than a single filter approach. Second, we evaluate the impact of using seabed auxiliary variables in the models compared to the case of using only platform variables since measurements of the former are not always available in offshore oil wells. Finally, we assess the impact of using gray-box models, for which steady-state data are used to improve modeling (Barbosa, Aguirre, Martinez, & Braga, 2011; Teixeira & Aguirre, 2011), compared to the case where only black-box models are used. Thus, it is important to clarify that this paper does not aim at providing an comprehensive comparison among soft sensor techniques, but it rather reports a well-succeeded experience of developing and implementing a soft sensor in an industrial framework.

This paper is outlined as follows. Section 2 briefly describes the process under investigation. Section 3 presents the two steps of the methodology employed. Then, Sections 4 and 5 discuss the experimental results. Finally, concluding remarks are presented in Section 6. A preliminary version of this paper appears as Teixeira, Barbosa, Gomes, Teixeira, and Aguirre (2012).

2. Process description

To produce oil from low pressure and/or deepwater oil wells, gas-lift technology is often employed. Fig. 2 presents a simplified diagram of a gas-lift oil well and Table 1 lists some of the process variables often measured. Except for TT1, TT4 and FT4, all variables listed in Table 1 are used to build models in this work. The PDG sensor provides measurements of PT1 and TT1.

The process is summarized as follows. Pressured gas from the gas-lift header at the platform (instruments tagged by 4) is injected through annulus between tubing and casing string until it reaches an orifice valve located in the lower part of the tubing