SPE 112046

Downhole Multiphase Metering in Wells by Means of Soft-Sensing

M. Leskens, B. de Kruif, S. Belfroid, SPE, and J. Smeulers, SPE, TNO Science and Industry, and
A. Gryzlov, Delft University of Technology

This paper was prepared for presentation at the 2008 SPE Intelligent Energy Conference and Exhibition held in Amsterdam, The Netherlands, 25–27 February 2008.

Abstract

Multiphase flow meters are indispensable tools for achieving optimal operation and control of wells as these meters deliver real-time information about their performance. For example, multiphase flow meters located downhole can improve the production of multilateral and multizone wells by timely allocating the zone where a gas or water cone occurs. However, multiphase meters are either expensive, inaccurate, or cannot be used downhole due to the harsh conditions. An alternative that can be used to overcome these disadvantages is to use multiphase *soft-sensors*, i.e. to *estimate* holdups and flow rates from relatively cheap and reliable conventional meters, such as pressure and temperature measurements, and a dynamic model connecting these measurements with the unknown quantities. The aim of this paper is to demonstrate, via two simulation based case studies, some possibilities and limitations of such multiphase soft-sensors. In the first case study the question is adressed whether it is possible to use only downhole pressure and temperatures measurements to estimate in real-time the water, oil and gas flow rates in a well. This question is of practical importance as these measurements are relatively cheap and reliable. The second case addresses the question whether it is possible to allocate the gas cone in a well with multiple inflow points or zones. This question is relevant as the estimated flow rate and holdup profiles can be used to manipulate Inflow Control Valves in such a way that gas breakthrough is prevented.

Using amongst others OLGA data as "real-life" data, an additional question addressed here is what the influence is of soft-sensor model error and measurement noise on the quality of the estimates.

From the first case study it can be concluded that, due to bad observability, pressure and temperature measurements alone are not sufficient to accurately estimate in real-time well flow composition parameters in a practically relevant situation. The preliminary results discussed in the second case study indicate that a soft-sensing solution to the gas cone allocation problem may very well be feasible.

Introduction

Motivated by the ever growing discrepancy between demand for and availability of oil and gas and by the improvement and increased availability of downhole measurement and control equipment, the oil and gas industry has recently embraced the "smart wells" philosophy. The main idea of this philosophy can be stated as the improvement of current reservoir management by improving current reservoir and well monitoring and control practice. By doing so, one aims at a higher yield from a given reservoir, on the short-term and/or on the long-term, while simultaneously fulfilling constraints that are imposed out of environmental and (other) operational considerations.

Here, the focus is on the improvement of current well monitoring practice. Well monitoring can be defined as real-time measuring or estimating well production performance parameters such as water, oil and gas flow rates. These can be delivered to an operator or a control system to allow for taking steps to improve current well production performance. In particular, monitoring devices located downhole can improve the production of multilateral or multizone wells by determining at which areas/zones of the well which fluids are entering. Even more specific, this knowledge allows for a better handling of gas or water breakthrough. See e.g. Leemhuis *et al.* (2007).

Well monitoring can, in principle, be performed by means of multiphase meters. However, current multiphase meters are either expensive, or inaccurate, or accurate only within a restricted operating range, or cannot be used downhole due to the harsh conditions over there. See e.g. Stewart (2002). An alternative that can be used to overcome all these disadvantages is to use multiphase *soft-sensors*, i.e. to *estimate* holdups and flow rates from conventional measurements and a dynamic well model connecting these measurements with the quantities to be estimated. When considering multiphase soft-sensors, relevant questions are (i) which soft-sensing techniques are available and (ii) which of them are suitable for multiphase metering, (iii) which measurements do they require, (iv) how to model the well for the purpose of multiphase soft-sensing, (v) do multiphase soft-sensors perform better than their regular counterparts, and (vi) are they capable of doing that cheaper? Although this paper provides at least to some extent answers to these questions, it is not its aim to provide complete and definite answers to all of them, if ever possible. Instead, the objective is to demonstrate, via two (separate) simulation based case studies, some possibilities and limitations of multiphase soft-sensors.

The first case addresses the question whether it is possible to use only downhole pressure and temperature measurements to estimate in real-time the water, oil and gas flows in a well. This question is of practical importance as pressure and temperature measurements are (viewed as) relatively cheap and reliable, thereby allowing for the multiphase soft-sensor to be a relatively cheap and reliable alternative for regular multiphase meters.

The second case addresses the flow allocation problem. More specific, it addresses the question whether, in case of multiple inflow points or zones, such as e.g. at a long horizontal well or in a multilateral well, it is possible to reconstruct the distributions of the flow rates over these inflow points or zones. This question is, for example, relevant for wells with severe chance on water or gas breakthrough at each of the inflow points: if one knows at which part of the well a gas or water cone approaches the well, one can close down the corresponding Inflow Control Valve (ICV) instead of having to shut down the well production completely by closing down the wellhead choke (see e.g. Leemhuis (2007)). Hence, such a multiphase soft-sensor would allow for better control of such wells with multiple inflow points.

An additional question that is addressed in both case studies is what the influence of model error and measurement noise is on the quality of the estimates.

Both case studies are simulation based and do not consider real-life well data. In order to mimic the situation of testing the considered soft-sensor with “real-life” data, and hence under soft-sensor model error, data from the commercially available dynamic multiphase flow simulator OLGA are used.

The oil and gas industry has already seen quite a number of soft-sensing applications. Many of them focus on estimating reservoir properties, such as permeabilities, via an Ensemble Kalman Filter (Evensen, 2003). See e.g. Wen and Chen (2005) and the work of Nævdal and co-workers (e.g. Nævdal and Vefring (2002) and Nævdal *et al.* (2003)). Other applications are more focused on well applications and involve gas-lift wells (Bloemen *et al.*, 2004) and underbalanced drilling (Lorentzen *et al.*, 2003). Another line that is followed uses black-box (empirical) modeling instead of rigorous modeling as e.g. in the Shell FieldWare Production Universe tool (see e.g. Cramer *et al.* (2006)). Although there are similarities between the work presented here and that discussed in these papers, the first differs from the latter with respect to the type of application that is considered and/or the type of soft-sensor that is applied.

The organization of the paper is as follows. First, soft-sensing is discussed. More specific, an overview is given of available soft-sensing methods and those that are applied in this paper are explained in more detail. Subsequently, the two case studies are discussed. At the end of this paper, the main conclusions of these case studies are summarized.

Soft-sensing

Overview of available methods

Soft-sensing (also called state estimation, data assimilation or model inversion) is used to estimate the non-measured. This is achieved by using measurements that *are* available and a model that describes the relation between these measurements and the quantities to be estimated. Several types of soft-sensing tools can be found in the literature. The most popular ones can be divided into two groups: (i) those based on probability theory and (ii) those based on numerical optimization (although under certain circumstances methods of these groups coincide). The most well known one of the first group is the Kalman filter (KF) (Kalman, 1960), which is the statistically optimal state estimator for linear systems subject to white Gaussian noise. Other state estimators belonging to this group are extensions to nonlinear systems of the (linear) Kalman filter known as (i) the Extended Kalman filter (EKF) (Jazwinski, 1970), (ii) the Ensemble Kalman filter (EnKF) (Evensen, 2003) and the Unscented Kalman filter (UKF) (see Julier *et al.* (2000) and Wan and van der Merwe (2000)). Also the so called particle filter (Gordon *et al.*, 1993) can be reckoned to this group. A soft-sensing technique belonging to the second group is the so called moving-horizon estimator (see e.g. Robertson and Lee (1995)).

Generally, the numerical optimization based soft-sensing tools perform best due to their optimal handling of nonlinearities and, in particular, *constraints*. However, these tools generally are also computationally most time-consuming. Because of the associated high computation time, numerical optimization based soft-sensing tools were not taken into account for multiphase metering. Instead, only probability theory based soft-sensors were considered, in particular nonlinear extensions of the Kalman filter. These will be discussed now in more detail.

Nonlinear extensions of the Kalman filter

In order to explain the idea behind Kalman filter (KF) based soft-sensors, assume that the process to be monitored is described by the nonlinear discrete-time system

$$x_{k+1} = f(x_k) + v_k \qquad (1)$$

with x_k the *state* of the system and v_k zero mean Gaussian white noise (ZMGWN). Additionally, assume that some or all of the states of this system are measured and that the corresponding measurements are also disturbed by ZMGWN:

$$y_k = h(x_k) + w_k \tag{2}$$

Here, y_k represent the measured outputs and w_k ZMGWN. The aim of any KF, or state estimator in general, is then to estimate the states x_k from the noisy output measurements y_k. It does that recursively over time, i.e. renewed at each new sampling instant *k* (when new output measurements becomes available), with each recursion consisting of the computation of the state estimate for the next sampling instant *k+1* using both the state estimate and measurements that are available at time *k*. Denoting the desired state estimate for *k+1* as $\hat{x}_{k+1|k}$, with the subscript "*j*|*i*" denoting "estimate for instant *j*, given output measurements available up till instant *i*", and the state estimate already available at instant *k* as $\hat{x}_{k|k-1}$, a KF proceeds as follows. First, a *measurement update* (MU) is performed, where the already available state estimate is upgraded to an improved estimate $\hat{x}_{k|k}$ using the new measurements y_k that have become available at instant *k*. A KF performs this MU step (*analysis* step in EnKF nomenclature: see Evensen (2003)) as

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + L_k(y_k - \hat{y}_{k|k-1}) \tag{3}$$

where L_k is the so called *Kalman gain* and $\hat{y}_{k|k-1}$ is a prediction of y_k given output measurements up till *k-1*. With *E[.]* representing the expectation operator, the optimal values for this prediction and gain, with optimal defined in *minimum mean-squared error* sense (see e.g. Anderson and Moore (1979)), are given as

$$\hat{y}_{k|k-1} = E\left[h(\hat{x}_{k|k-1}) + w_k\right] = E\left[h(\hat{x}_{k|k-1})\right] + 0 = E\left[h(\hat{x}_{k|k-1})\right] \tag{4}$$

and

$$L_k = P^{xy}_{k|k-1}(P^{yy}_{k|k-1})^{-1} \tag{5}$$

where $P^{xy}_{k|k-1}$ and $P^{yy}_{k|k-1}$ represent the following *error covariance* matrices:

$$P^{xy}_{k|k-1} = E\left[(x_k - \hat{x}_{k|k-1})(y_k - \hat{y}_{k|k-1})^T\right] \tag{6}$$

$$P^{yy}_{k|k-1} = E\left[(y_k - \hat{y}_{k|k-1})(y_k - \hat{y}_{k|k-1})^T\right] \tag{7}$$

Having obtained the estimate $\hat{x}_{k|k}$ at the measurement update step, a KF proceeds to perform a second step denoted as the *time update* (TU) step (*forecast* step in EnKF nomenclature) where the desired state estimate $\hat{x}_{k+1|k}$ is computed from $\hat{x}_{k|k}$ using the system equations (1). The optimal TU step equations are given as

$$\hat{x}_{k+1|k} = E\left[f(\hat{x}_{k|k}) + v_k\right] = E\left[f(\hat{x}_{k|k})\right] + 0 = E\left[f(\hat{x}_{k|k})\right] \tag{8}$$

A KF requires additional error covariance update equations in order to be complete. These have been left out here, however, for reasons of space and can be found in the mentioned references. The KF also needs the covariance matrices for v_k and w_k as input. Ideally, these covariance matrices are given. However, in practice, these matrices are generally unknown and are, thereby, determined in a trial-and-error way by means of tuning.

The various KF types found in the literature differ with respect to the way the optimal MU and TU equations given above are implemented. In the linear model case, the equations above can be further elaborated to arrive at the optimal linear KF equations: see e.g. Kalman (1960) or Anderson and Moore (1979) for this derivation. The EKF *approximates* the optimal KF equations by using $E\left[h(\hat{x}_{k|k-1})\right] \approx h(\hat{x}_{k|k-1})$ in the MU equations and $E\left[f(\hat{x}_{k|k})\right] \approx f(\hat{x}_{k|k})$ in the TU equations and, additionally, by using the model Jacobians $\frac{df}{dx_k}(x_k = \hat{x}_{k|k})$ and $\frac{dh}{dx_k}(x_k = \hat{x}_{k|k-1})$ for approximating the error covariance update equations. The EnKF and UKF approximate the optimal KF equations by replacing the expectations in these equations for *sample* means and sample covariances (though not at places where linearity of the equations does not require them to be replaced): $E[h(\hat{x}_{k|k-1})] \approx \frac{1}{N}\sum_{i=1}^{N} h(\hat{x}^i_{k|k-1})$, $E[f(\hat{x}_{k|k})] \approx \frac{1}{N}\sum_{i=1}^{N} f(\hat{x}^i_{k|k})$, etc., where $\hat{x}^i_{k|k-1}$ and $\hat{x}^i_{k|k}$ are *a priori* chosen realizations of the random variables $\hat{x}_{k|k-1}$ resp. $\hat{x}_{k|k}$. The difference between the EnKF and the UKF lies in how these realizations are selected: the EnKF does that in a random way to create an *ensemble* of such realizations, whereas the UKF does that in a specific deterministic way using the so called *unscented transformation* (Julier *et al.*, 2000) with the selection being such that means and covariances are guaranteed to be computed accurately up to third order.

When comparing the EKF, EnKF and UKF, the latter two perform approximately equally well and better than the EKF due to the fact that the EnKF and UKF better handle system nonlinearities. When nonlinearities are relatively small, however, the EKF performs similarly as the other two. With respect to computation time, the EKF and UKF computation times depend on the number of model states (the size of x_k), denoted here as n, while the EnKF computation time is more or less fixed and depends on the chosen ensemble size. More specific, the EKF computation time is typically of the order of n model simulations (Nævdal and Vefring, 2002), the UKF computation time approximately of order 2*n model simulations and the EnKF computation time is approximately of the order of $N_{ensemble}$ model simulations, with $N_{ensemble}$ being the EnKF ensemble size (typically in the order of 100). As a result, the EKF is always approximately two times faster than the UKF and both these filters are faster than the EnKF for low order systems (n<50). For higher order systems (n>100), however, the EnKF is fastest. Apart from handling nonlinearities and computation time, a third factor in choosing between the EKF, EnKF and UKF is the ease of implementation, including tuning. In that respect, the EnKF seems to be better than the other two as the UKF requires tuning of additional parameters and the EKF requires the computation of Jacobians.

In this paper, only the EKF and the EnKF are considered. In case study 1 only the EKF is considered. This type of soft-sensor was chosen because of its relatively fast computation time for low order systems, which are the type of well models considered in this case study (most of the times n = 15). Nevertheless, it still was necessary to speed up the calculations to get the EKF computation time below the required sample time. This was achieved by using a computationally cheap approximation to the model Jacobian. How this cheap Jacobian approximation was computed is, for completeness, briefly stated in the appendix of this paper. For case study 1 the EnKF was found to be too slow. In case study 2 only the EnKF was considered. The main reason for that was its relative ease of implementation while still.being computationally fast enough.

Estimating model parameters that are not states

The quantities to be estimated are not always contained in the state vector x_k. Instead, they may be included simply as parameters d_k in the model:

$$x_{k+1} = f(x_k, d_k) \tag{9}$$

If one wants to (also) estimate these model parameters by means of one of the soft-sensing methods discussed above, one needs to incorporate somehow these quantities into the state vector of the model. A simple and most of the times effective way to do that is as follows:

$$\begin{bmatrix} d_{k+1} \\ x_{k+1} \end{bmatrix} = f_{ext}(x_k, d_k) = \begin{bmatrix} d_k \\ f(x_k, d_k) \end{bmatrix} \tag{10}$$

Instead of *f(…)*, now, the extended model $f_{ext}(\ldots)$ is the model used in the soft-sensor. In the case studies discussed in this paper, the unknown model parameters were estimated in this way.

Case 1: Soft-sensing with only pressure and temperature measurements

The measurements that are mostly applied downhole in wells are pressure and temperature measurements. This can be subscribed to their relatively cheapness and reliability. A practically relevant question is, therefore, whether one can estimate, with some soft-sensor, the multiphase flow properties from these measurements alone. The aim of the first case study is to provide an answer to this question.

The setup that has been chosen to answer this question is schematically depicted in Figure 1.

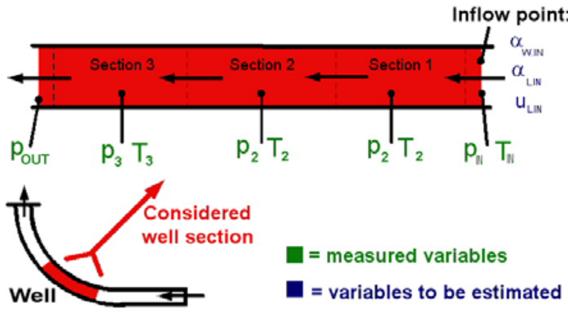

Figure 1: Setup for case 1

A section of a single well is considered (see lower left corner of Figure 1 for the single well considered and upper part of this figure for the considered section). The aim is to estimate, by means of a soft sensing technique, the composition of the flow entering this section (at the inflow point in Figure 1), i.e. water, oil and gas flow rates. More specific, this should be done with a limited set of pressure (p) and temperature (T) measurements along the considered well section only. In order to fullfil this aim, a dynamic model should be obtained that connects the p & T measurements with the quantities to be estimated. This was established by dividing the considered well section into several serially connected sections for each of which the water, liquid and gas mass balance are solved together with the mixture momentum balance. Also, in order to account for the difference in velocity between gas and liquid, a drift-flux model was added. The results discussed here are obtained with a drift-flux model formulation due to Brill and Mukherjee (1999). It must be noted, though, that other drift-flux models also were used, such as e.g. the one due to Shi *et al.* (2004), and that the final, qualitive conclusions given here for case 1 were found not to depend on the particular drift-flux model. Without going into further detail, the final well section model that was obtained was of the form of

$$
\begin{aligned}
x_{k+1} &= f(x_k, d_k) \\
y_k &= h(x_k, d_k)
\end{aligned}
\qquad (11)
$$

with d_k containing the unknown inflow point composition variables to be estimated and y_k containing the measured variables. Instead of chosing the unknown inflow point composition variables as flow rates, it was found to be more convenient to implement them as water holdup $\alpha_{W,IN}$, liquid holdup $\alpha_{L,IN}$ and liquid velocity $u_{L,IN}$ (see also figure 1). All other model parameters (such as e.g. friction factors) were assumed to be known, including (liquid) densities, so that from the mentioned compositon parameters the corresponding water, oil and gas flow rates could be readily computed. Some of the model parameters are given in table 1 to give an idea about the well section model considered in the simulations to be discussed.

Table 1: Well section model parameters for case 1

Length [m]	360
Diameter [m]	0.1714
Pressure at inlet [bar]	150
Pressure at outlet [bar]	140
Inclination, section #1, 2 & 3 [degr]	5, 15 & 25

An EKF with a computationally cheap approximation to the model Jacobian, as explained above and in the appendix, was used as soft-sensing technique. In the results to be discussed here, a sample time of 30 seconds was chosen for the EKF and measurements. This was thought to be sufficiently fast to capture all relevant well dynamics *c.q.* dynamics in the time varying inflow composition parameters. Many simulations were performed with other sample times, though, within the range of 1 to 60 seconds. The results from these simulations did not alter the final qualitative conclusions given for this case. Without going into further detail, it was found that tuning of the EKF (i.e. choosing the covariance matrices for the disturbances v_k and w_k: see the previous section) was not straightforward and time consuming.

The EKF was first tested under the ideal condition that no uncertainty at all, in the form of measurement noise and model error, was present. For that purpose, measurement data were simulated, using some random realizations for the well inflow parameters, with the same well section model (11) that was used in the EKF. The configuration used in this comparison is schematically depicted in Figure 2.

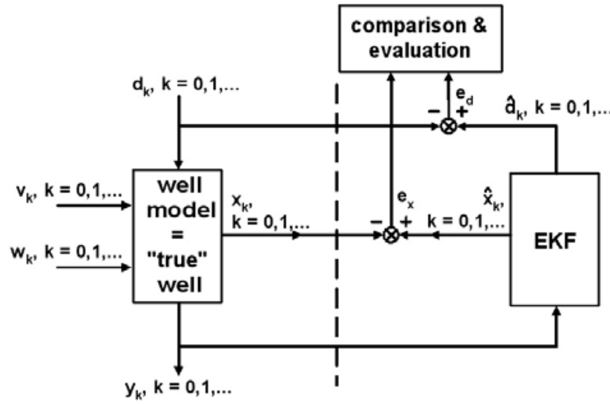

Figure 2: EKF performance evaluation setup

It is noted that during the first EKF performance evaluation tests v_k and w_k were held equal to *0* for all time *k* (no uncertainty). The performance tests comprised three typical situations that could be encountered during the operation of a well: (i) normal well conditions, which were assumed to correspond to relatively slowly varying inflow composition parameters, (ii) the occurrence of a gas cone, and (iii) the occurrence of a water cone. During these tests it was, first of all, observed that the well section model should consist of at least three sections, as depicted in Figure 1, in order to be able to obtain consistent estimates for the well inflow composition parameters. As a result, a minimum of five p-measurements and four T-measurements (the latter because of the particular structure of the well section model) should be used to obtain such estimates. Secondly, in all three situations mentioned just above, the performance of the EKF (with three sections in the well section model) was found to be very well, indicating that it should in principle be possible to use only p- and T-measurements to obtain good estimates of the flow composition parameters at some section of the well. See e.g. figure 3. It is noted that the remaining model states were equally well estimated and that the estimation results for occurrence of a gas cone (not shown here) were similarly good.

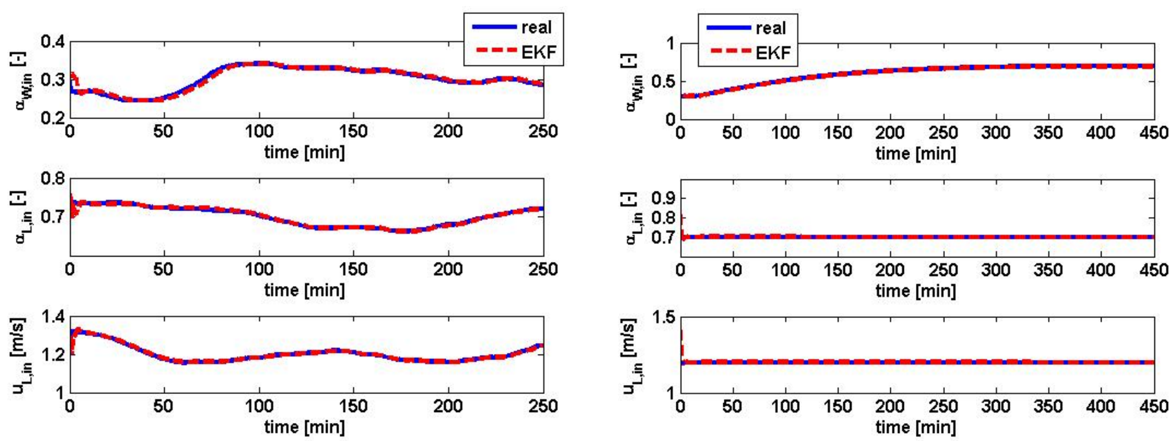

Figure 3: The performance of the EKF under no uncertainty for (left:) (assumed) normal well operating conditions, i.e. for relatively slowly varying well inflow composition parameters, and (right:) uncertainty in case of water breakthrough (sharp and large increase in water holdup).

However, when measurement noise was added, i.e. nonzero w_k, to the "true" well (see Figure 2) during the simulation, the results became unsatisfactory. A very large amplification of the measurement noise to the estimates was observed, effectively making them useless for determining the true inflow composition parameters. See Figure 4, in particular the periods $t < 250$ *[min]* and $t > 1500$ *[min]*.

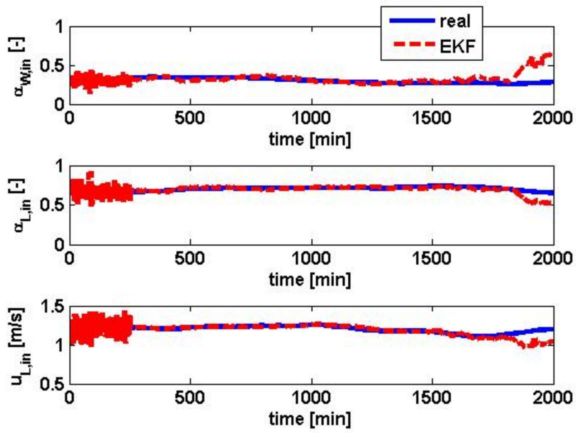

Figure 4: Soft-sensing with only p- and T measurements with measurement noise (MN). Period *0 <t< 250*: very low level MN and no low pass filtering (LPF) applied to the measurements. Period *250<t<1500*: very low level MN + LPF. Period *1500<t<2000*: higher but still low level MN + LPF.

This means that even for a very low level of measurement noise, very noise and even divergent estimates may be obtained. When the noise is very low, its effect on the estimates can be largely diminished by means of (heavy) low pass filtering of the measurements. See the period *250 < t < 1500 [min]* in Figure 4. However, for somewhat higher but still low levels of measurement noise also this low-pass filtering does not help anymore and, again, a large amplification of the measurement noise to the estimates is obtained. See the period *t >1500 [min]* in Figure 4. All this implies that in practical situation, where always some reasonable (i.e. not extremely low) amount of measurement noise is present, the soft-sensor is useless as it is then not able to provide accurate estimates for the well inflow composition parameters.

What, then, causes this large amplification of measurement noise to the estimates? This is subscribed to the model being badly *observable*, which is a technical term stating to what extent, for a given model, estimates of the states can be obtained from the available measurements. For linear models an observability measure is readily available which is typically a rank or a condition number test on some matrix computed from the model equations. For nonlinear models, however, such a measure is not readily available. In order to overcome the latter problem, the linear condition number test was applied to linearized matrices of the nonlinear well section model. It turned out that these condition numbers were very large, i.e. typically in the order of 10^4 – 10^6, thereby indicating that at least the linearized well section model was badly observable. This was interpreted, though, as the original, nonlinear, well section model also being badly observable.

It is noted that the bad observability and the uselessness of the EKF in real-life applications was confirmed by simulations with the particle filter (Gordon *et al.*, 1993), which is more accurate than the EKF but also slower (in fact, too slow for our application), under similar conditions as the simulations with the EKF were performed. Problems due to bad observability are also expected when significant model errors are present. This has not been investigated, though.

Observability problems can be solved by adding new measurements. First simulations with (only) an extra p- and T-measurement (by adding a new section to the well section model) did not solve these problems, however. It is expected, though, that, for example, adding a water amount measurement can make the well section model well observable. Future research is aimed at rendering the model well observable by adding new measurements.

Case 2: Soft-sensing for gas cone allocation under model error.

The second case study addresses the question whether it is possible to allocate, with multiphase soft-sensing techniques, gas breakthrough in a well with multiple inflow points, such as a multilateral or multizone well or a long horizontal well. This knowledge may improve the operation of such wells, as one can then shut down the particular section of the well where breakthrough has occurred by means of an ICV, instead of having to shut down the complete well. Furthermore, this case study provides an assessment of the influence of model error on the soft-sensing estimation results.

The case study is a preliminary study to the question addressed above and does not aim to provide a definite and complete answer to this question. Instead, it aims to provide a first assessment of a particular soft-sensing solution as an answer to this question. Being a preliminary study, some simplifications were made of which the most important ones are given below.

The simulation setup is schematically depicted in Figure 5. The test case considered deals with oil/gas flow in a part of a horizontal well. Due to numerical discretization used, there are 20 potential inflow points where both oil and gas can enter the wellbore. However as a simplification it is assumed that only at one inflow point a gas (no oil) is entering the well. In fact, this entering gas flow, Φg in Figure 5, represents a gas breakthrough at the well at 40 [m] at at the time period 1200 [s] < t < 3000 [s]: see Figure 5. The use of 20 inflow points implies 20 available pressure measurements, while oil and gas flow rate can be monitored only at the outflow of the well. It is the aim of the soft-sensor to allocate this gas flow *c.q.* cone, i.e. to estimate its size and position, given the mentioned measurements.

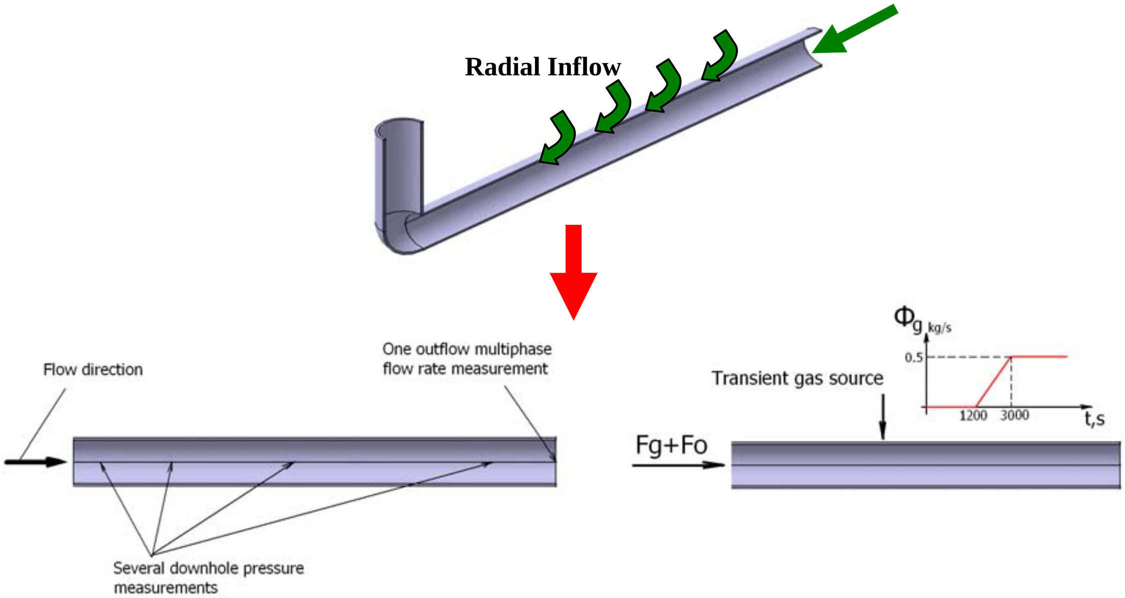

Figure 5: Setup for case 2

A similar soft-sensing evaluation setup was used as depicted in Figure 2 for case study 1. An important difference, however, was that the “true” well was not the same as the model used in the soft-sensor: the “true” well data were obtained from the OLGA simulator while a self-made multiphase flow model was used in the soft-sensor. This was done to assess the effect of (the inevitable) model error on the soft-sensor estimation results.

The two-phase liquid-gas flow model used in the soft-sensor was based on, amongst others, the work of Ouyang and Aziz (2000), Shoham (1982) and Vicente *et al*. (2001). It was obtained by (again) solving mass and momentum balances. A particularly important modeling assumption that was made was that of a dispersed bubble flow regime, with gas and liquid phases being well mixed and, therefore, slip between gas and liquid phases being negligible (Vicente *et al.*, 2001). Some parameters of the model are given below in table 2 to give an idea about the case discussed here.

Table 2: Model parameters for case 2

Length [m]	100
Diameter [m]	0.0508
Fo,inf [kg/s]	9.5
Fg,inf [kg/s]	0.5
Pressure at outlet [bar]	100

The model used in the soft-sensor was different from the OLGA model used to create the “true” well data. The main differences between these models, i.e. sources of model error, are assumed to be the following ones:

- Gas PVT data;
- Friction factor correlation;
- Numerical method error;

The EnKF was used as soft-sensor. As mentioned above, this was done because of its (relative) ease of implementation while also being computationally fast enough. The ensemble size that was used was equal to $N_{ensemble} = 100$.

The results from the soft-sensor evaluation are depicted in Figure 6. The total simulation time here is 3600 [s] with sample time for the measurements being equal to 60 [s]. The results show that the proposed soft-sensor, for the given simplified setup, is very well capable of reproducing the flow rate and holdup distributions along the considered well part, even under model error. Thereby, as can be seen from the upper left and lower part of Figure 6, it also is able to detect the gas cone entering the well.

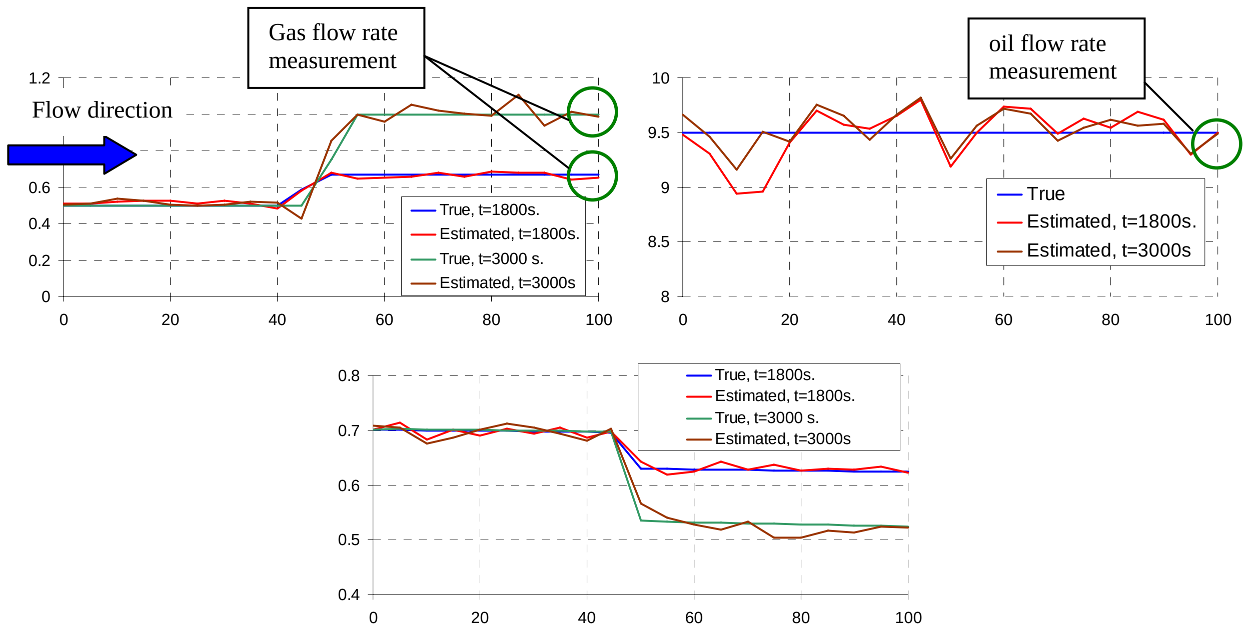

Figure 6: Comparison of estimated and true values for case 2: upper left = estimated versus true gas mass flow rates; upper right = estimated versus true oil mass flow rates; below = estimated versus true liquid holdup. The pictures depict for two time instances, i.e. for t = 1800 [s] and t = 3000 [s], the distributions of the flow rates and holdup along the length of the considered well part

The setup considered is still a simplified version of reality. Future work is aimed at assessing the soft-sensor performance for a more realistic situation, in particular a situation where every inflow point has an oil and gas flow entering the well.. Also, as another simplification, no measurement noise was present on the estimation data. Its effect on the quality of the estimates is also still subject of further research. Additionally, future work includes (i) further improvement of the model, (ii) testing of the soft-sensor against truly true well data and (iii) integration into a gas coning control framework as proposed in, for example, Leemhuis *et al.* (2007).

Conclusions

By means of two case studies, some limitations and possibilities of soft-sensor multiphase meters have been discussed. The first case study addressed the question whether it is possible to use only downhole pressure and temperatures measurements to estimate in real-time the water, oil and gas flow rates in a well. It was shown that when no model error or measurement noise is present, this is very well possible. However, when measurement noise is present, this is not possible. This is subscribed to the bad observability of the well section model that is considered. This observability problem can be solved by adding new measurements. Future work is, therefore, aimed at this possibility, thereby aiming to make the soft-sensor practical applicable.

The second case addresses, in a two phase formulation, the question whether it is possible to reconstruct the distributions of the oil and gas flow rates along a well and, thereby, to allocate the inflow of certain fluids in specific location along this well. The, still preliminary, results indicate that this is possible, even under model error, by using only downhole pressure measurements and two individual surface flow measurements. This, in turn, is a promising result from, for example, a gas coning control point of view.

Acknowledgements

This paper discusses results that have been obtained as part of an ongoing research project within the field of “smart wells” denoted as ISAPP, which is a joint research project of Shell, TNO and Delft University of Technology. The authors would therefore like to thank the ISAPP Knowledge Centre for making this paper possible. The authors would also like to thank Wouter Schiferli (TNO Science and Industry) for performing the OLGA runs.

References

Anderson, B.D.O. and Moore, J.B. "Optimal Filtering", Prentice Hall, 1979.

Bloemen, H.H.J., Belfroid, S.P.C., Sturm, W.L. and Verhelst, F.J.P.C.M.G. "Soft Sensing for Gas-Lift Wells", SPE paper 90370, SPE Annual Technical Conference and Exhibition, Houston, Texas, USA, 2004.

Brill, J.P. and Mukherjee, H. "Multiphase Flow in Wells", Monograph Vol. 17, SPE Henry L. Dohorty Series, 1999.

Cramer, R, Moncur, C. and Berendschot, L. "Well-Test Optimization and Automation", SPE paper 99971, SPE Intelligent Energy Conference and Exhibition, Amsterdam, The Netherlands, 2006.

Evensen, G. "The Ensemble Kalman Filter: theoretical formulation and practical implementation", Ocean Dynamics 53, pp. 343-367, 2003.

Gordon, N.J., Salmond, D.J. and Smith, A.F.M. "Novel approach to nonlinear/non-Gaussian Bayesian state estimation", Radar and Signal Processing, IEE Proceedings F, Vol. 140, Nr. 2, pp. 107-113, 1993.

Jazwinski, A.H. "Stochastic Processes and Filtering Theory", Academic Press, 1970.

Kalman, R.E. "A New Approach to Linear Filtering and Prediction Problems". Trans. ASME, Journal of Basic Engineering, Vol. 82 (Series D), pp. 35-45, 1960.

Leemhuis, A.P., Belfroid, S.P.C. and Alberts, G.J.N. “Gas Coning Control for Smart Wells”, SPE paper 110317, SPE Annual Technical Conference and Exhibition, Anaheim, California, USA, 2007.

Lorentzen, R.J., Nævdal, G. and Lage, A.C.V.M. "Tuning of parameters in a two-phase flow model using an ensemble Kalman filter", International Journal of Multiphase Flow 29(8), pp. 1283-1309, 2003.

Nævdal, G. and Vefring, E.H. "Near-Well Reservoir Monitoring Through Ensemble Kalman Filter", SPE paper 75235, SPE/DOE Improved Oil Recovery Symposium, Tulsa, Oklahoma, USA, 2002.

Nævdal, G., Johnsen, L.M., Aanonsen, S.I. and Vefring, E.H. "Reservoir Monitoring and Continuous Model Updating Using Ensemble Kalman Filter", SPE paper 84372, SPE Annual Technical Conference and Exhibition, Denver, Colorado, USA, 2003.

Ouyang, L.B., Aziz, K. “A Homogeneous Model for gas-liquid Flow in Horizonal wells”, Journal of Petroleum Science and Engineering, 27, pp. 118-128, 2000.

Robertson, D.G. and Lee, J.H. "A least squares formulation of state estimation", Journal of Process Control 5(4), pp. 291-299, 1995.

Shi, H., Holmes, J.A., Diaz, L.R., Durlofsky, L.J. and Aziz, K. "Drift-Flux Parameters for Three-Phase Steady-State Flow in Wellbores", SPE paper 89836, SPE Annual Technical Conference and Exhibition, Houston, Texas, USA, 2004.

Shoham, O. “Flow pattern transition and Characterization in Gas-Liquid Two-Phase Flow in Inclined Pipes”, PhD dissertation, Tel Aviv U., Israel, 1982.

Stewart, D. “Multiphase metering today”, Offshore Engineer, December 2002.

Julier, S., Uhlmann, J. and Durrant-Whyte, H.F. "A new method for the nonlinear transformation of means and covariances in filters and estimators", IEEE Transcations on Automatic Control 45(3), pp. 477-482, 2000.

Vicente, R. Sarica C., Ertekin T. ”A Two-Phase Model Coupling Reservoir and Horizontal Well Flow Dynamics”, SPE paper 69570, SPE Latin American and Caribbean Petroleum Engineering Conference, Buenos Aires, Argentina, 2001.

Wan, E.A. and van der Merwe, R. "The Unscented Kalman Filter for Nonlinear Estimation", in: Proc. of IEEE Symp. on Adaptive Systems for Signal Processing, Communication and Control (AS-SPCC), Lake Louise, Alberta, Canada, 2000.

Wen, X.-H., and Chen, W.H. "Real-Time Reservoir Updating Using Ensemble Kalman Filter", SPE paper 92991, SPE Reservoir Simulation Symposium, Houston, Texas, USA, 2005.

Appendix: a computationally cheap approximation of the Jacobian

In order to provide a computationally cheap method of approximating the Jacobian of the model equations $\frac{df}{dx_k}(x_k)$, which can be used as $\frac{df}{dx_k}(x_k = \hat{x}_{k|k})$ in the EKF to increase its computational speed, it is first noted that the discrete-time model $x_{k+1} = f(x_k)$ for which the Jacobian is to be derived is assumed here to be derived from a continuous-time counterpart denoted as $\frac{dx}{dt} = \tilde{f}(x)$, through integration over an (sample) interval $t=[0, T_s]$. It additionally is noted that $\frac{df}{dx_k}(x_k)$ can be obtained as the solution for $\frac{dx}{dx_k}(t)$ at $t = T_s$ of the initial value problem (IVP)

$$\begin{cases} \dfrac{dx}{dt} = \tilde{f}(x); & x(0)=x_k \\ \dfrac{d}{dt}\left(\dfrac{dx}{dx_k}\right) = \left(\dfrac{d\tilde{f}}{dx}(x)\right)\left(\dfrac{dx}{dx_k}\right); & \dfrac{dx}{dx_k}(0)=I \end{cases} \tag{A.1}$$

with I the identity matrix. The idea behind obtaining the computationally cheap Jacobian approximation, now, is to use the constant matrix $A_C = \dfrac{d\tilde{f}}{dx}(x=x_k)$ in (A.1) as an approximation for $\dfrac{d\tilde{f}}{dx}(x)$, which is not constant due to its dependence on x. By doing so, $\dfrac{df}{dx_k}(x_k)$ is approximated by the solution at T_s of the IVP

$$\frac{d}{dt}\left(\frac{dx}{dx_k}\right) = A_C\left(\frac{dx}{dx_k}\right), \qquad \frac{dx}{dx_k}(0)=I \tag{A.2}$$

This solution can be cheaply obtained (and independent from the solution x to the model equations) either by using the analytical solution to (A.2) or as the system matrix of a numerically computed discretized version of (A.2), denoted here as A_d. Note that this discretized version is equal to

$$\left(\frac{dx}{dx_k}\right)_{k+1} = A_d\left(\frac{dx}{dx_k}\right)_k; \qquad \left(\frac{dx}{dx_k}\right)_k = I \tag{A.3}$$

and that, hence, the solution to this problem at $k+1$ is equal to $\left(\dfrac{dx}{dx_k}\right)_{k+1} = A_d * I = A_d$ and, furthermore, that this solution also represents the desired approximation of $\dfrac{df}{dx_k}(x_k)$.

The matrix $A_C = \dfrac{d\tilde{f}}{dx}(x_k)$ can be cheaply obtained from the continuous-time model equations $\tilde{f}(x)$, at x_k, either analytically or numerically via some perturbation approximation.

In the results discussed in case study 1, the Jacobian $\dfrac{df}{dx_k}(x_k)$ used by the EKF is approximated as discussed above by A_d with A_C approximated by a forward finite difference approximation applied to the continuous-time model equations and with A_d obtained from this matrix via a zero-order-hold discretization method available in the software package used for the computations. A 20 time reduction in computation time has been observed with the application of the cheap Jacobian approximation.