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ASSESSMENT OF UNCERTAINTIES AND PARAMETER ESTIMATION IN A OFFSHORE GAS PIPELINE

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Abstract: Oil production in Brazil has turned its attention to the Santos basin in recent years because it is the most promising national oil province. Despite the crisis facing the operating companies due to the current low commercial value of the barrel, it is expected output growth in this region. It is an offshore basin with many of different reservoirs, with a strategy to start production in a short period of time. For the flow of natural gas associated with the production of this oil are being built infrastructure consisting of pipelines, reaching a total of over 700 km long, and gas processing plants on land. The concept applied in the development of these fields, which prioritizes the anticipation of production fields, follows the concept of main pipelines where production units are connected and export natural gas. The operation of this gas pipeline is based on numerical models for calculation of intermediate properties, future behavior prediction and estimates the capacity of the integrated flow. These models are based on assumptions for parameters as heat exchange and field sensors of boundary conditions such as pressure, flow rate, temperature and composition of the natural gas. This paper presents the development proposed for state and parameter estimation based on the implementation of an extended Kalman filter, to determine appropriate values the parameters of the flow and use of complementar sensors in boundary conditions. The proposed flow model, necessary to the Kalman filter, is one-dimensional, transient, compositional and capable of solving complex networks, being based on the mass, momentum, species and energy conservation, and uses as closing equations the equation of state proposed by Peng-Robinson and single-phase friction factor. The partial derivative of the flow model, necessary for the construction of the Jacobian matrix state of propagation and measurement, are obtained numerically. The state vector consists of parameters to be estimated and boundary conditions where there is direct measuring are considered as control vector, which reduces the state vector size and mathematical complexity involved. The other flow properties are defined only by the flow model across the flow profile. Results are compared for three months field data in the pipeline, which is subject to frequent pigging operations. These results are compared to different state estimation. The results show reduced systematic error between simulated and measured at the Kalman filter application for state estimation and reduction of deviation between calculated and measured values when using Kalman filter to estimate parameters when compared to conventional methods. This best fit and smaller deviation leads to better accuracy in calculate intermediate properties and predicting behavior, possibility a reducing in tolerances applied to the operating limits. Future developments of this work are application in more complex gas flow network and evaluation of the concept for synthetic data with known values for the parameters to be estimated and leakage.

Keywords: Uncertainties, estimation, Kalman filter, gas pipeline, offshore technology

NOMENCLATURE

Flow

ρ : Specific mass
Re : Reynolds Number
v : Speed
P : Pressure
t : time
T : Temperature
D : Diameter
g : Acceleration of gravity
θ : Angle with horizontal
f : Friction factor
X : Molar Fraction
H : Fluid Specific Enthalpy
$\dot{Q}$: Heat transfer

Kalman filter

F : Matrix of the state transition model
x : State vector
u : Control vector
w : process noise
B : Matrix of the control inputs model
Q : Model noise matrix
R : Observation noise matrix
I : Identity Matrix
K : Kalman optimal gain matrix
P : Model covariance matrix
z : State observation vector
H : state observation matrix
v : Observation noise

Modifiers

X_k : Variable X at current time
X_{k-1} : Variable X at the instant of previous time
$X_{k|k-1}$: Prediction for variable X at the current instant based on the previous time
$X_{k-1|k-1}$: Prediction for variable X at the previous time
$X_{k|k-1}$: Prediction for variable X based on the previous time
$X_{k|k}$: Estimate for variable X based on the current time

INTRODUCTION

Oil production is associated with natural gas production. There is a need for the destination of this gas, which is more expensive than the destination of liquids and even more in the offshore production. To address this issue, there are the possibilities of gas reinjection into the reservoir or exporting it through gas pipelines to natural gas treatment plants onshore. This exporting demands the construction of gas pipelines of large diameters and lengths, with long installation time and high associated costs .

As a strategy to reduce installation time and cost, the natural gas flow system constructed in Brazilian Santos Basin is composed of large main gas pipelines to which the units connect through flexible pipes. This brings a greater complexity in flow behavior and management, by absence of underwater instrumentation on subsea equipments.

To help this operation, numerical tools calculate the local flow conditions in these pipelines (Rasheed, 2011), with a wide variety of commercial software available for this. These codes can also periodically calculate the flow variables based on the field sensors available for input and output of involved actors in a configuration called Pipeline Management System, or PMS.

These systems are based on sensors available for use in predetermined boundary conditions of the flow model, and adjustable parameters, such roughness or thermal exchange coefficient, to minimize errors in dependent variables. Some of the adjustment forms are PID controllers or algebraic calculations (Hanmer, 2012). Those approaches cause difficulties when adjusting simultaneous parameters, or mixing pressure and flow rate measured at the same point (Hoeven, 1987).

As redundant sensors are available in field applications, is interesting to develop techniques that allow the use of these additional data. Estimation theory allows use of these redundant measures to estimate flow condition in pipeline, in addition to allowing inference on unmeasured parameters. This task can be performed by a Kalman filter, a recursive estimator that considers the existence of uncertainties in dynamical model and plant sensors.

This work describes the implementation of a Kalman filter to estimate flow parameters of a simple pipeline with one fluid inlet and one fluid outlet, and compares the results with traditional techniques applied in the pipeline operation.

FLOW MODEL

The first requirement for the implementation of a Kalman filter is building a model of the process. In this work, flow in pipelines is considered single-phase, one-dimensional, transient, thermal, compositional in a single pipeline with only one inlet and one outlet.

Conservation Laws

For the proposed flow, the model is based on three conservation equations, described below.

Continuity Equation

The first equation is the conservation of mass, described as

$$\frac{\partial \rho}{\partial t} + \frac{\partial (\rho v)}{\partial x} = 0 \tag{1}$$

Momentum Equation

The second is conservation of momentum. In its more traditional form, we can find it

$$\frac{\partial (\rho v)}{\partial t} + \frac{\partial \left(\rho v^2\right)}{\partial x} + \frac{\partial P}{\partial x} = -\rho g \sin\theta - \frac{1}{2} f \rho \frac{v|v|}{D} \tag{2}$$

Energy Equation

The third is conservation of energy. Although the intrinsic thermal effects are negligible, control equipment in the pipeline can cause significant temperature variation, thus justifying the inclusion of energy conservation in the model

$$\frac{\partial \rho \left(H + v/2 + gy\right)}{\partial t} + \frac{\partial \rho v \left(H + v/2 + gy\right)}{\partial x} = \dot{Q} - \dot{W}_{vc} \tag{3}$$

For the purposes of numerical solution, this non-linear equation in terms of temperature and pressure is linearized with a state equation.

Species Conservation

Since monitoring of composition is necessary, species conservation is also calculated,

$$\frac{\partial (\rho X_i)}{\partial t} + \frac{\partial (\rho v X_i)}{\partial x} = 0 \tag{4}$$

Due to its low influence on the flow, the compositional calculations can be solved separately from the previous equations, without issues to numerical convergence.

Closing Equations

For the solution of conservation equations is necessary calculate intermediate properties of the flow, like compressibility of the fluid and friction between fluid and the pipeline.

State Equation

As equation for the calculation of fluid properties the Peng & Robinson (1976) correlation,

$$p = \frac{RT}{V-b} - \frac{a\alpha}{V^2 + 2bV - b^2} \tag{5}$$

widely used in applications involving natural gas.

Friction factor

The pressure drop is quite simple considering only one phase. The concept of pressure drop for single-phase flow, with friction factor are used. An explicit equation

$$\frac{1}{\sqrt{f}} = -2.\log_{10}\left(\frac{k}{3,7D} + \frac{5,74}{R_e^{0,9}}\right) \tag{6}$$

The friction factor explicit equation proposed by Swamee-Jain (1976) was used instead.

Numerical Scheme

Equations are modified for convenient variables, discretized with use of the Finite Volume Method (Maliska, 1995), and numerically solved with the aid of sparse matrices solver based on LU decomposition. The flow fields are calculated, then species are calculated, and the iterative process runs until convergence. Assembled matrices are sparse and almost diagonal, reducing effort required for inversion. Each row of the matrices corresponds to one conservation equation or boundary condition equation. First conservation equations are assembled for each discretization point and then boundary equations are assembled for nodes. This is the motivation for the division of the elements of flow network into pipelines, where flow occurs, and nodes, where boundary conditions are applied.

$$\begin{pmatrix} A_{1,1} & A_{2,1} & \dots & A_{n,1} \\ A_{1,2} & A_{2,2} & \dots & A_{n,2} \\ \vdots & \vdots & \ddots & \vdots \\ A_{1,n} & A_{2,n} & \dots & A_{n,n} \end{pmatrix} \cdot \begin{pmatrix} X_1 \\ X_2 \\ \vdots \\ X_n \end{pmatrix} = \begin{pmatrix} B_1 \\ B_2 \\ \vdots \\ B_n \end{pmatrix} \tag{7}$$

With application of this solution method, an initial condition and boundary conditions are required for calculating the variables in a later time step. This is convenient for computation of partial derivatives necessary to estimate the state vector, with high efficiency in the parallelism of calculation.

STATE ESTIMATION

The approach proposed in this work applies a Kalman filter to a nonlinear flow problem, for the sensor fusion, detection of systematic errors in sensors and estimation of flow parameters. To validate the proposed approach, a comparison with the results provided by the Method of Similar Errors will be performed. This method adjusts flow rate and pressure at the same point based on assumed errors for each of the measurements.

Algebraic Method

The use of state estimation for natural gas flow goes back to Hoeven (1987), with several more works Modisette (2009, 2011, 2013). The method predicted that the differences between measurement and calculation would be managed by an error to be defined, a for the input and output of natural gas flows.

$$\frac{P_i^{modeled} - P_i^{sensor}}{\sigma_i^P} = \frac{Q_i^{modeled} - Q_i^{sensor}}{\sigma_i^Q} \tag{8}$$

The adjustment of one variable depends on the error in other, based in predefined deviations, σ_i. This leads to systematic errors for adjustments, or an error propagation, changing the calculated inventory for pipeline.

Extended Kalman Filter

The Kalman filter is an optimal stochastic recursive estimator that minimizes the covariance of the estimation error in a least-squares sense. Uncertainties in the deterministic models of the plant and of measurement considered by the addition of white zero-mean Gaussian noise. In the case of non-linear applications, the so called *Extended Kalman Filter* provides the necessary framework to tackle the problem. In this version, the non-linear model is linearized around the newest estimate of the state. However, due to the linearization, the extended version is a sub-optimal estimator. This drawback is mitigated by the tracking ability of the estimator, that can detect sudden changes in the dynamics of the system. The discrete system and measurement models, according to Gelb (1974), are given by the following equations:

Model

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

$$z_k = h(x_k, v_k) \tag{10}$$

Prediction

$$\hat{x}_{k|k-1} = f(\hat{x}_{k-1|k-1}, u_k) \tag{11}$$

$$P_{k|k-1} = F_{k-1} P_{k-1|k-1} F_{k-1}^{\top} + Q_k \tag{12}$$

Correction

$$\tilde{y}_k = z_k - h(\hat{x}_{k|k-1}) \tag{13}$$

$$S_k = H_k P_{k|k-1} H_k^{\top} + R_k \tag{14}$$

$$K_k = P_{k|k-1} H_k^{\top} S_k^{-1} \tag{15}$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k \tilde{y}_k \tag{16}$$

$$P_{k|k} = (I - K_k H_k) P_{k|k-1} \tag{17}$$

Jacobian

$$F_{k-1} = \left. \frac{\partial f}{\partial x} \right|_{\hat{x}_{k-1|k-1}, u_k} \tag{18}$$

$$H_k = \left. \frac{\partial h}{\partial x} \right|_{\hat{x}_{k|k-1}} \tag{19}$$

Although the Kalman filter is a great numerical tool for estimating status, it is still just a tool. The success of its application and stability in results depends on the way this tool is used. For the characteristics of the problem of interest, the strategy to be developed consider modifications in the model as state vector, while intermediate variables and boundary conditions are control vector.

CASE

The pipeline under study is a real one, with about 175 km long and 16 inches in diameter facility in operation for more than 25 years. This pipeline has an exporting unit that put fluid on inlet and a gas treatment plant receiving the pipeline fluid on outlet. The flow is biphasic, as the unit produces gas and condensate from two different fields. The production is offshore and the water depth is about 180 m. The volumetric gas flow rate practiced in this pipeline is $1.2MMNm^3/d$, with a condensate flow rate of $400m^3/d$, varying according to the configuration of producing wells, operating difficulties, planned maintenance in the gas treatment unit or in the production plant and several other factors, configuring a flow with great transient effects.

The gas treatment unit is onshore and has a simple dew point adjusting device. Both units involved, the production one and the treatment one, operates with flow rate control, and so the numerical model counts with the same boundary conditions. This is a transient calculation, and the estimated state converges to the real one due to the use of state estimation.

This pipeline is subject to frequent pigging operations to control liquid inventory, and this operations changes pressure at the outlet of pipeline. This effect is not considered on the model proposed.

The flow geometry used, as well as properties of this pipeline, are given in table 1.

Table 1 – Pipeline Geometry

L [m]	**dy [m]**	**D [in]**	**Roug[mm]**	**U** [$\frac{J}{Km^2}$]	**T**$_{amb}[C]$
200	0	16	0.183	50	18
200	-200	16	0.183	50	18
175000	200	16	0.183	50	18
200	0	16	0.183	50	18

The field sensors available for this pipeline are pressure, flow rate and temperature at inlet and outlet of pipeline, while the gas composition is taken periodically by gaseous chromatography. The sensor at inlet of pipeline is considered the gold-standard and major errors are allocated at the outlet of pipeline, on the gas treatment unit.

In Figure 1 a schematic drawing of the pipeline in study is shown. It consists of one gas pipeline without diameter variations.

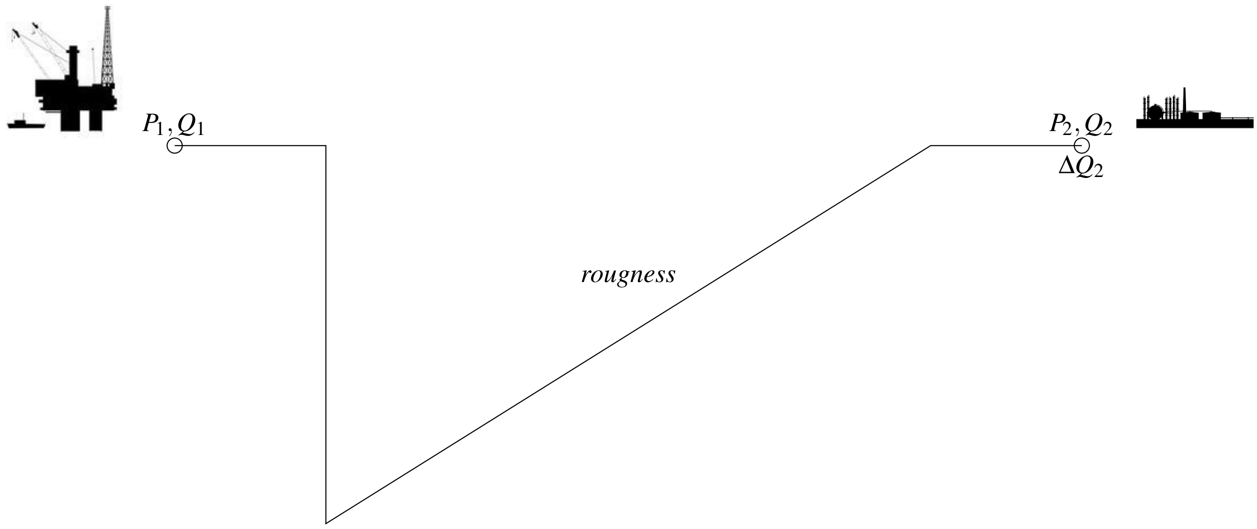


Figure 1 – Pipeline schematic

With the observations described above, the model for study of pipeline and its inlet and outlet conditions was definer, according to Figure 1. Due to the low influence and simplification of the problem, temperature will not be treated in this case. To evaluate the influence of the pressure drop on pipeline, a state vector are proposed including mechanism for change in pressure drop due to friction effects and an offset for outlet flow rate.

The observation vector used in the Kalman filter

$$z = \begin{bmatrix} P_1 \\ Q_1 \\ P_2 \\ Q_2 \end{bmatrix} \tag{20}$$

includes the measured variables that defines the flow in pipeline:

The state vector will be compound by two state variables: the differential flow rate ΔQ_2 at the output and the roughness of pipeline. The first variable is justified to eliminate continuity problems in flow. The other one is an adjustment of pressure drop through the absolute roughness of the pipeline.

$$x = \begin{bmatrix} \Delta Q_2 \\ Rougness \end{bmatrix} \tag{21}$$

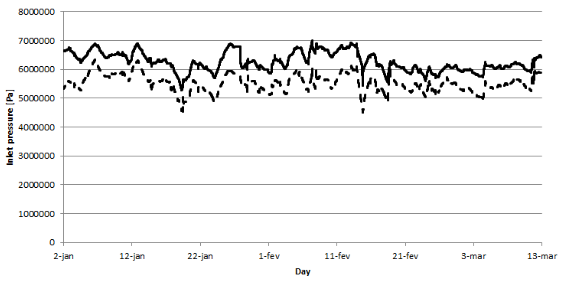
RESULTS

In this section results will be presented for the State Estimation of the two cases proposed, to allow an validation of gains related to the algebraic method and Kalman filtering cases. Since these are results obtained from experimental values of a real pipeline, the real value to roughness is unknown.

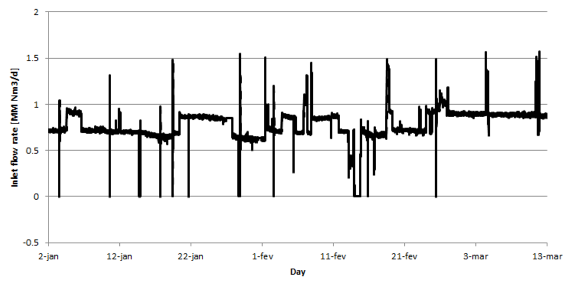
The comparison is based on measured and calculated values of flow rate and pressure for the inlet and outlet of the pipeline. Histograms of the difference between these values are presented to compare the quality of results. The closer the results, the better the state estimation.

Similar errors method and PID

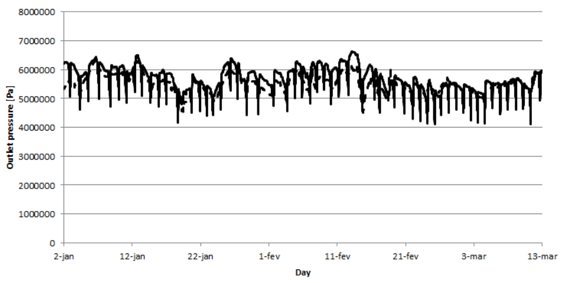
To compare the evolution of the state estimation technique, a simulation was performed for study case using the similar errors method, in which the pressure and flow at the pipeline outlet were adjusted. The period used was 3 months. Figure 2 compares the input and output pressures and flows rates. Trends are similar between the estimated state, in continuous line, and the field sensor, in segmented line.



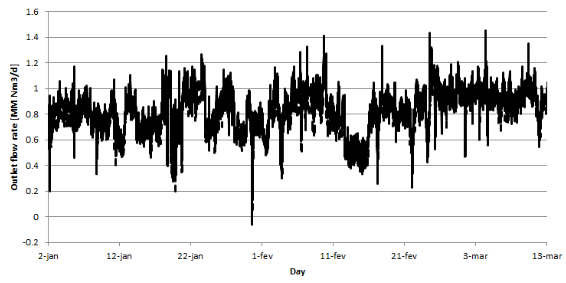
(a) Inlet pressure



(b) Inlet flowrate



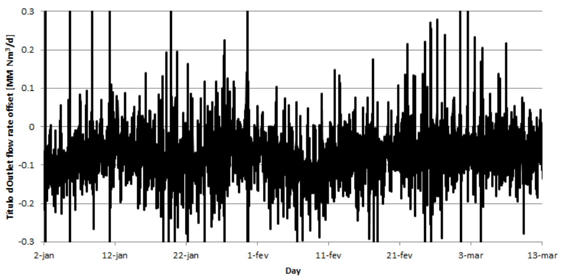
(c) Outlet Pressure



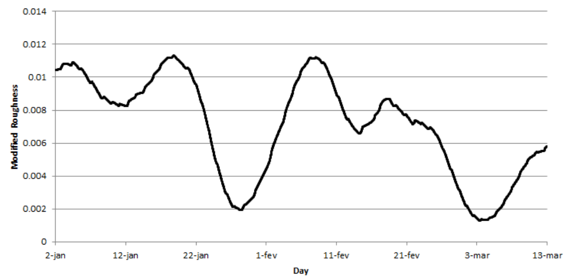
(d) outlet Flowrate

Figure 2 – Pressures and flow rates results for method of similar errors

Figure 3 shows the results for the estimated measurement offset and modified roughness values. Solution for similar errors is stable, but the parameter estimated was not. The modified roughness estimation does not find a stable value with more than three months of simulations.



(a) ΔQ_2



(b) Rougness

Figure 3 – Estimated parameters

From the results we verify that there is stability in solution, but with the existence of systematic errors, necessary for the adjustments of the method. This error was allocated at the exit of the pipeline, but the technique allows to allocate also in other points, or even in several points, weighting according to defined σ values. In figure 4 we see the result for normalized error between calculated values and sensors over time.

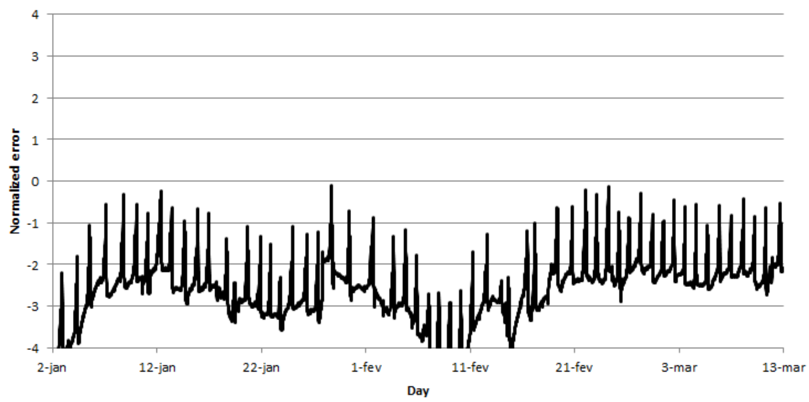


Figure 4 – Normalized Error

The standard deviation of curve in 2 is 1.71, and its average value is -1.65. This averaged error is related to error propagation in this method. For comparison, the histogram of the error in the results in continuous line and the normal curve best fitted to it, in segmented line, are shown in figure 5.

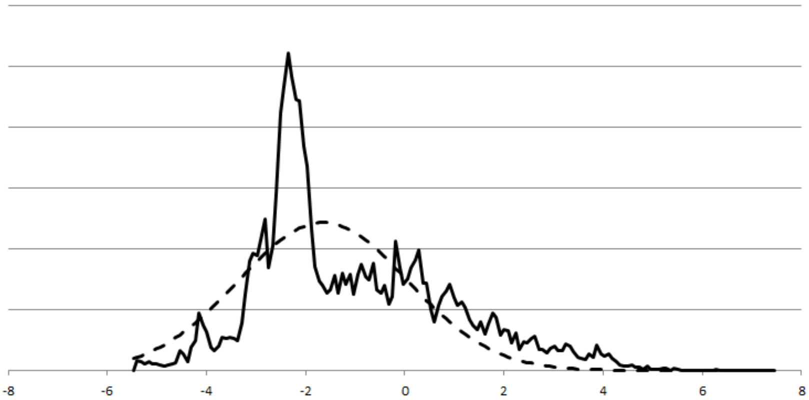


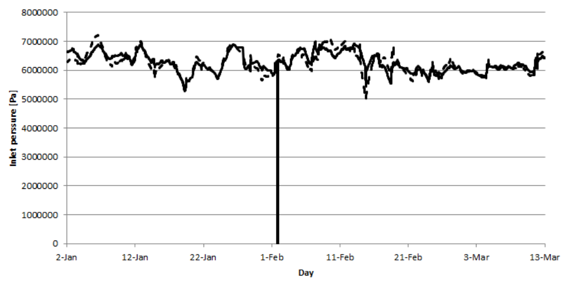
Figure 5 – Histogram for study case using the method of similar errors

This approach is efficient when the model is used to predict rising or falling pressure depending on unit outages (Modissete, 2004). And, because it is an algebraic solution, it does not increase the computational cost of the simulation. However, to monitor molecules in the flow or to assert that inventory is insufficient, since it has error propagation in profile of estimated pressures, with direct influence on calculated inventory.

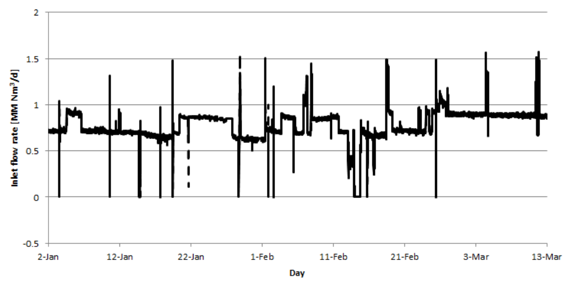
Kalman filtering

This case aims to determine if results obtained are consistent with what was expected by the known physics of the problem. In figure 6 we check and compare the inlet and outlet pressures and flow rates. Trends are similar between the estimated state, in continuous line, and the field sensor, in segmented line.

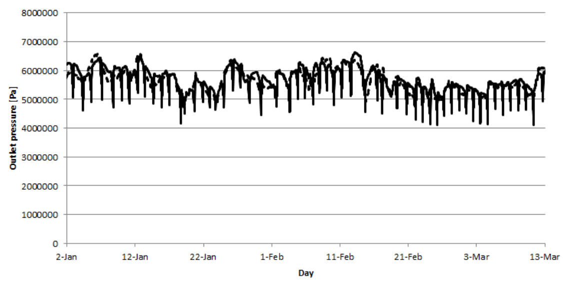
The curves are closer than those of previous case, and there is no systematic difference between curves of pressures, only of flow rate of output. This demonstrates the existence of an offset in this variable, compatible with observations of the real pipeline.



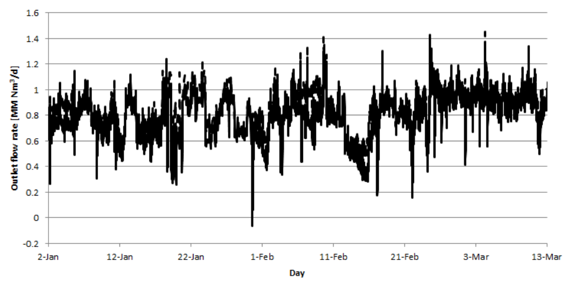
(a) Inlet pressue



(b) Inlet flowrate



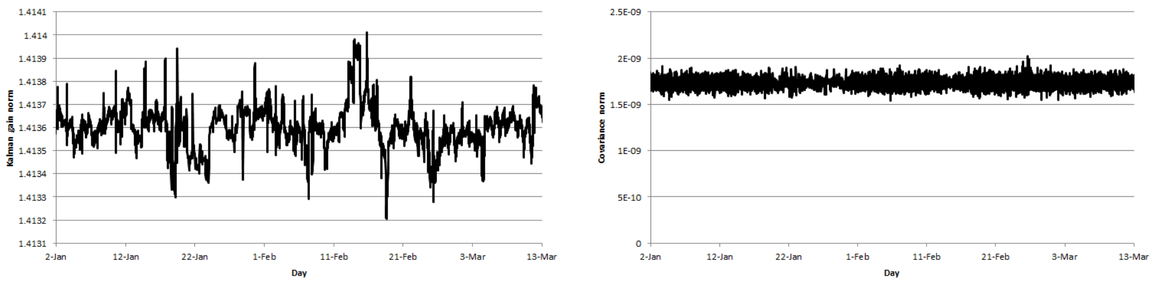
(c) Outlet pressure



(d) Outlet pressure

Figure 6 – Pressures and flow rates results for Kalman filtering

Figure 7 present the Euclidean norms of the Kalman gain and error covariance matrices. Norms have stable behavior, without great variations in time.



(a) Kalman gain norm

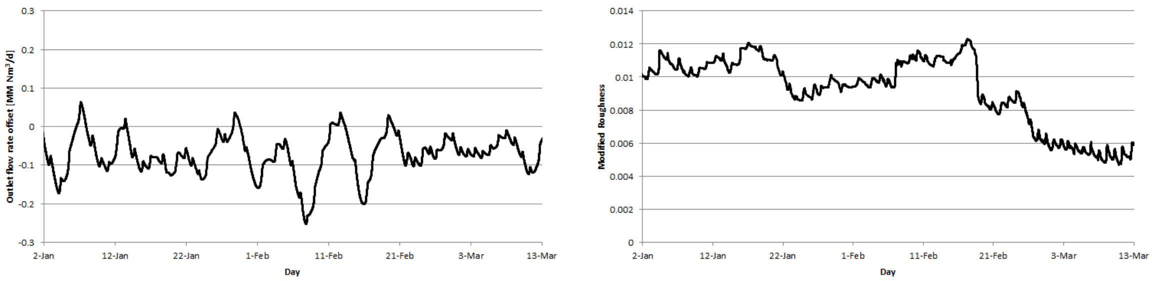
(b) Covariance error norm

Figure 7 – Euclidean norms

There are two estimated parameters, the modification in pipeline output flow rate and modified roughness. The results for parameter estimation are shown in figure 8.The correct value for the estimated parameters are unknown, but an initial value adjustment and a relative stabilization after some time are expected.

During the simulation period, communication failures occurred between the estimator and the field readings. The solution has been stable even under these conditions and was better able to predict the pressure and flow rate at inlets and outlets of pipeline, as expected for the Kalman filter application.

The estimated parameters have low amplitude and high frequency oscillation, in principle related to pigging operations. However, the estimated value for the change in the outflow of the pipeline is close to the value obtained by means of large intervals, or -0.05 , compatible with results of the previous case. The additional parameter estimated, or roughness, showed an initial stabilization, and a change of threshold. This behavior cannot be explained by a change in the physical roughness of pipeline, being probably related to other parameters that influence the pressure drop in pipeline.



(a) ΔQ_2

(b) Rougness

Figure 8 – Estimated parameters

Differences between the estimated states and field sensors, normalized by the Euclidean norm of the noise matrix of sensors are presented in figure 9. The error associated with the state is greater when influenced by pigging operations, but is still less than three times the standard deviation for the field measurements as expected.

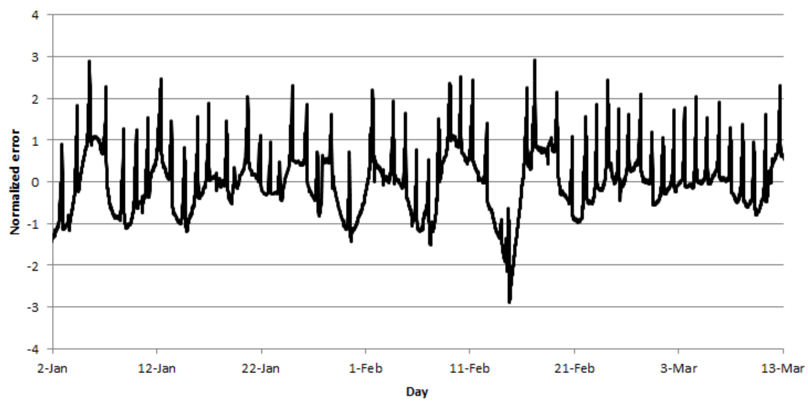


Figure 9 – Normalized error

The histogram of this case, in continuous line of figure10, reveals that the average found was zero as expected (Modisette, 2009). The best fit of a normal curve for this histogram is in segmented line. The standard deviation of this normal curve is 0.639 , and the mean value is zero. The adjustment of parameter for the pressure drop, or the adjusted roughness, had no influence on the error mean, behavior expected since it acts on the pressure drop adjustment.

The standard deviation was reduced by fifteen percent by using Kalman filtering comparing to the algebraic techniques, and a change in the difference between the calculated and measured pressures are observed, with good overlap in inlet and outlet pressures.

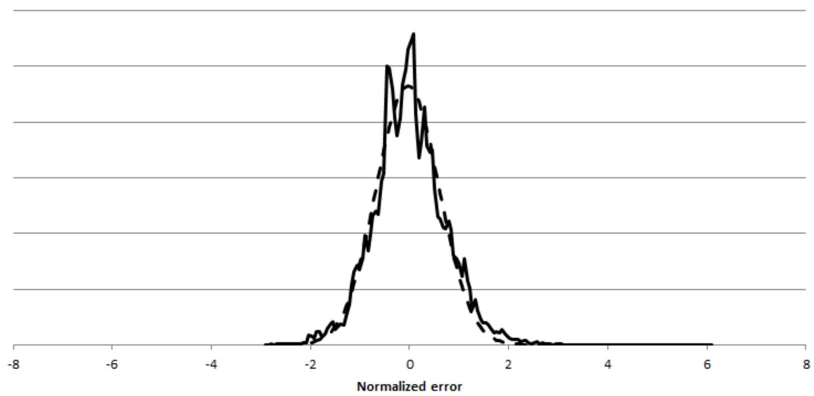


Figure 10 – Histogram for study case using Kalman Filtering

CONCLUSIONS

The results show an improvement of state estimation with Kalman filter when compared to algebraic method available in literature, without systematic errors for adjustments and error propagation to other variables. In addition, the estimated parameters of systematic error in the sensors and equivalent roughness for the flow show a suitable trend for these parameters, with low variation once adequate values are reached.

On the other hand, the computational cost to calculate the state is increased significantly with the application of extended Kalman filter, by the necessity of determining the local derivatives in the model which are performed numerically (Modisette, 2009). This effect must be taken into account for using Kalman filtering.

Based on the results found for simple pipeline, a similar approach is being developed for more complex gas pipelines, which currently operates with two gas treatment units and eight exporters, also from Brazilian Santos Basin, and with more than 400 km long.

Future work may also seek explanations for behavior of gain and covariance matrices for better definition of filter properties. Another need is the structuring of mechanisms for construction of the model noise matrices and measurements. A third possibility of development is the migration to a multiphase flow model, allowing the pigging operations. Finally, a discussion of the most appropriate approximations for measurement offset is still necessary.

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