V European Conference on Computational Fluid Dynamics
ECCOMAS CFD 2010
J. C. F. Pereira and A. Sequeira (Eds)
Lisbon, Portugal, 14–17 June 2010

OPTIMAL HEATING CONTROL TO PREVENT SOLID DEPOSITS IN PIPELINES

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Key words: Flow Assurance, Pipeline Heating System, Optimal Control

Abstract. *Heat transfer analysis in oil and gas pipelines is of major importance for the prediction and prevention of paraffinic deposits and hydrate formations, which can interrupt the oil and gas flow and result in large financial losses. This is specially the case for deep sea pipelines used in offshore production. In such pipeline, hydrates can be formed, even at relatively high temperatures within the oil-gas-water mixture pumped from the production wells, due to the high pressures involved. Traditional methods to prevent paraffinic deposits and hydrate formations are generally based on thermal insulation, depressurization of the line, injection of hot dead oil, pigging and injection of chemical inhibitors. Recently, active heating systems have been under study to maintain the fluid temperature above a critical value in order to avoid the formation of solid deposits. The main objective of this paper is to examine an optimal control approach for a typical heating system during shutdown conditions. A quadratic cost functional is minimized through the solution Riccati´s equation.*

1 INTRODUCTION

Offshore oil production has constantly become more challenging for several reasons, including among others, the increasing length of deep-sea pipelines required for the oil transportation from wells to platforms [1]. The thermal performance of such subsea systems is critical, because the produced fluid cannot undergo significant temperature reductions as it flows in the pipeline at high pressures [2]. Therefore, flow assurance is a key point for the design of subsea petroleum systems in deepwater. Its analysis involves the prevention and control of solid deposits that can originate inside the production fluid, as a result of heat transfer to the surroundings. Therefore, heat transfer analyses in petroleum and gas pipelines are extremely important for the prediction and prevention of paraffinic wax deposits and hydrate formations, which can interrupt the flow and cause large financial losses (figure 1) [3].

There are different kinds of deposits that can be formed in pipelines used in offshore production. The physical and chemical characteristics of the produced fluids may facilitate the accumulation of natural gas hydrates, wax, and other substances. These accumulations may cause reduction of flow area and increase the wall roughness, thus increasing the head loss and reducing the flow capacity [4]. Traditional methods to manage the solid deposits are generally based on depressurization of the line, injection of hot dead oil, pigging and injection of chemical inhibitors. However, one of the main strategies to mitigate flow assurance issues is to minimize heat losses from the system by using thermal insulation and/or active heating [5].

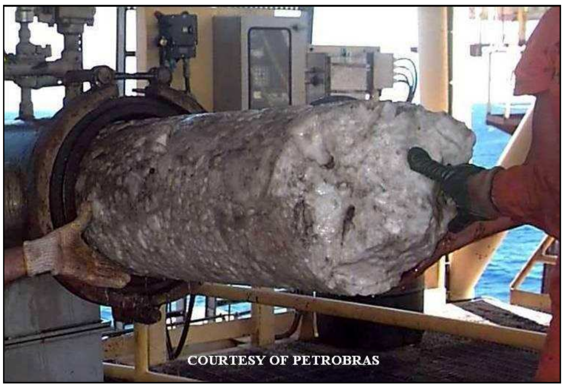


Figure 1: Hydrate block

Thermal insulation layers are added to the pipeline in order to maintain a minimum temperature of the flowing fluid. On the other hand, when passive thermal insulation is not sufficient to prevent solid deposits development in the system, active heating is required to maintain the fluid temperature above a critical value.

The main objective of this paper is to examine an optimal control approach for a heating system used to avoid the fluid temperature drop, during typical production shutdown conditions. The control is based on temperature measurements supposedly available on the external surface of the pipeline, which are used to reconstruct the temperature field inside the fluid via the solution of an inverse problem of state estimation. The state variables are considered as the transient temperatures within a pipeline cross-section and the state estimation problem is solved recursively with the Kalman filter [11-15]. The temperatures predicted with the Kalman filter are then utilized in a control approach for a heating system used to maintain the temperature within the pipeline above the critical temperature causing the formation of solid deposits. The pipeline is heated through its external surface and the imposed heat flux is considered as the control variable. A linear quadratic controller is utilized in this work and the associated quadratic cost functional is minimized through the solution of Riccati’s equation [6].

2 PIPELINE HEATING SYSTEM

In subsea fields, the relatively hot petroleum (at temperatures as high as 80 ^{o}C) is extracted from wells located on the bottom of the ocean, which can be 2000-3000 meters deep. The surrounding seawater at this depth is at a temperature of approximately 4 ^{o}C, thus causing significant cooling of the petroleum flowing through long pipelines on the ocean floor. The temperature of the produced fluid needs to be maintained above the critical value in the entire pipeline in order to prevent the formation of solid deposits. If the steady flow conditions are interrupted due to a system shutdown, a transient heat transfer analysis is then needed to establish the time period that the produced fluid temperature is above such critical temperature. During this time period, the operators are required to reach a decision in terms of the necessity to use the available technologies to avoid the formation of solid deposits. From the practical experience, it has been observed that the need for the injection of chemical inhibitors of solid deposits in the pipeline is considerably reduced when heating is utilized. The pipeline can be heated by several methods, but typical concepts are based on the so-called direct electrical heating system (DEH) [7] and indirect electrical heating system (IEH) [8]. In the direct electrical heating system, electric current flows axially through the pipe wall causing Joule heating in the fluid. On the other hand, in the indirect electrical heating system, the electrical current flows through heating elements (e.g., one or more electrical cables) on the pipe surface.

3 PHYSICAL PROBLEM AND MATHEMATICAL FORMULATION

The idealized problem considered in this work consists of the cross-section of a pipeline, represented by a circular domain filled with a stagnant fluid, thus not taking into account the pipe wall. The fluid is considered as homogeneous, isotropic and with constant thermal properties. The direct heating system described above is assumed for this analysis. The heat flow rate resulting from Joule’s effect is considered in the form of a transient heat flux appearing in the boundary condition of the fluid domain.

This idealized pipeline will be treated here as a linear transient heat conduction problem in a single medium. By also considering axial symmetry, the dimensionless formulation of this heat conduction problem in cylindrical coordinates is given by

$$\frac{\partial\theta(R,\tau)}{\partial\tau}=\frac{\partial^2\theta(R,\tau)}{\partial R^2}+\frac{1}{R}\frac{\partial\theta(R,\tau)}{\partial R} \qquad 0\le R<1,\ \tau>0 \tag{1.a}$$

$$\frac{\partial\theta(R,\tau)}{\partial R}+Bi\,\theta(R,\tau)=Q(\tau) \qquad R=1,\ \tau>0 \tag{1.b}$$

$$\theta(R,0)=1 \qquad 0\le R<1,\ \tau=0 \tag{1.c}$$

where the following dimensionless groups were defined:

$$\theta(R,\tau)=\frac{T(r,t)-T_\infty}{T(r,0)-T_\infty} \tag{2.a}$$

$$\tau = \frac{\alpha t}{r^{*2}} \tag{2.b}$$

$$R = \frac{r}{r^*} \tag{2.c}$$

$$Bi = \frac{h r^*}{k} \tag{2.d}$$

$$Q(\tau) = \frac{r^*}{k(T(r,0) - T_\infty)} q(t) \tag{2.e}$$

Here, T_∞ is the surrounding environment temperature, h is the convective heat transfer coefficient, k and α are the fluid thermal conductivity and diffusivity, respectively, r^* is the external radius, Bi is the Biot number and $q(t)$ is the uniform heat flux imposed on the external surface resulting from the direct heating.

The mathematical formulation governing the heat conduction problem given by eqs. (1-2), was solved with the finite volume method [10]. The computer code developed for this purpose was verified by using an analytical solution obtained with the Classical Integral Transform Technique.

4 STATE ESTIMATION AND OPTIMAL CONTROL

State estimation problems are used to predict the time varying state of a dynamical system, based on observations $\mathbf{z}_k$ obtained during the evolution of the system, as well as on a model for the system evolution for the state variables $\boldsymbol{x}_k$. This model, known as evolution model, together with the observation model, constitutes the state space representation of the dynamical system [6, 11, 12].

The vector $\boldsymbol{x}_k \in R^n$ is called the state vector and contains the variables to be dynamically estimated. The vector advances in time in accordance with the state evolution model, defined in the form

$$\boldsymbol{x}_k = \mathbf{f}_k\,(\boldsymbol{x}_{k-1}, \boldsymbol{u}_{k-1}, \mathbf{v}_k) \tag{3}$$

where $\mathbf{f}$ is, in the general case, a non-linear function of the state variables $\boldsymbol{x}$, of the control input to the system $\boldsymbol{u}$ and of the state noise or uncertainty vector $\mathbf{v}_k \in R^n$.

The observation model describes the dependence between the state variable and the measurements $\boldsymbol{z}$ through the general, possibly non-linear, function $\mathbf{h}$, given by

$$\mathbf{z}_k = \mathbf{h}_k\,(\boldsymbol{x}_k, \mathbf{n}_k) \tag{4}$$

where $\mathbf{z}_k \in R^m$ are available at times t_k, k=1, 2, 3, …. The vector $\mathbf{n}_k \in R^m$ represents the measurement noise or uncertainty.

For the classical linear time-invariant discrete state estimation problem, the evolution model is written in the form

$$\boldsymbol{x}_k = \mathbf{A}\boldsymbol{x}_{k-1} + \mathbf{B}\boldsymbol{u}_{k-1} + \mathbf{v}_k \tag{5}$$

where $\mathbf{A}$ is the linear evolution matrix of the state variable $\boldsymbol{x}$ and $\mathbf{B}$ is the input matrix. The state uncertainty or noise $\mathbf{v}_k$ is assumed to be a Gaussian random variable with zero mean and covariance **F**.

The linear observation equation is given in the form

$$\mathbf{z}_k = \mathbf{C}\mathbf{x}_k + \mathbf{D}\mathbf{u}_{k-1} + \mathbf{n}_k \tag{6}$$

where $\mathbf{z}_k$ is the measurement vector, $\mathbf{C}$ is the linear observation matrix and **D** is the direct transmission matrix. The observation noise $\mathbf{n}_k$ is assumed to be a Gaussian random variable with zero-mean and known covariance **G**. The state and observation noises are assumed to be mutually independent.

In the application under study, the evolution model is given by the finite-volume representation of Eqs. (1.a-c). The state vector $\mathbf{x}_k$ contains the values of the temperatures at each of the volumes and the control variable $\mathbf{u}_k$ is given by the heat flux imposed on the boundary. Uncertainties in the evolution model come from the fact that different quantities in the formulation are not exactly known, such as the Biot number. A typical control to a pipeline heating system aims at keeping the fluid temperature above the critical temperature for the formation of deposits. Such critical temperature is approached by the fluid during cooling periods, such as production shutdown.

For the application of the control strategy in accordance with the optimum control theory for linear problems, the evolution and observation models are considered to be deterministic and given by [6, 11,12]:

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{u} \tag{7}$$

$$\mathbf{z} = \mathbf{C}\mathbf{x} + \mathbf{D}\mathbf{u} \tag{8}$$

where the dot superscript represents the time derivative.

For the case under analysis in this work, the aim of the associated optimal control problem is to find the control inputs $\mathbf{u}_k$ (the boundary heat flux) that minimizes the difference between the fluid temperature field and a desired profile $\mathbf{r}_k$. Thus, for the implementation of the control strategy we consider [6, 11]:

$$\bar{\mathbf{u}}_k = \mathbf{u}_k - \mathbf{u}^* \tag{9}$$

$$\bar{\mathbf{x}}_k = \mathbf{x}_k - \mathbf{x}^* \tag{10}$$

where $\mathbf{u}^*$ and $\mathbf{x}^*$ refer to the steady values of the control input and state variables, respectively. Hence, $\bar{\mathbf{x}}_k$ and $\bar{\mathbf{u}}_k$ are considered as deviations from their steady state values.

In terms of the linear quadratic regulator problem, the optimal values of the control input $\bar{\mathbf{u}}_k$ are obtained by minimizing the following quadratic cost functional [6, 11]

$$J = \int_{t_i}^{t_f} (\bar{\mathbf{x}}^T \mathbf{Q} \bar{\mathbf{x}} + \bar{\mathbf{u}}^T \mathbf{R} \bar{\mathbf{u}})\, d\tau \tag{11}$$

where the weighting matrices $\mathbf{Q}$ and $\mathbf{R}$ are symmetric positive definite.

The solution to the optimal control problem is the state feedback control law [6, 11]

$$\bar{\mathbf{u}}_k = -\mathbf{K}\bar{\mathbf{x}}_k \tag{12}$$

where the discrete-time state feedback gain **K** is of the form

$$\mathbf{K} = (\mathbf{R} + \mathbf{B}^T\mathbf{S}\mathbf{B})^{-1}\,\mathbf{B}^T\mathbf{S}\mathbf{A} \tag{13}$$

The matrix **S** is the steady state solution to the discrete-time *Riccati* equation

$$\mathbf{S}_k = \mathbf{A}^T\mathbf{S}_{k+1}\mathbf{A} + \mathbf{Q} - \mathbf{A}^T\mathbf{S}_{k+1}\mathbf{A}\mathbf{B}(\mathbf{R} + \mathbf{B}^T\mathbf{S}_{k+1}\mathbf{B})^{-1}\,\mathbf{B}^T\mathbf{S}_{k+1}\mathbf{A} \tag{14}$$

In the steady state, $\mathbf{S}_{k+1} = \mathbf{S}_k = \mathbf{S}$, and the above equation becomes

$$0 = \mathbf{A}^\mathbf{T}\mathbf{S}\mathbf{A} - \mathbf{S} + \mathbf{Q} - \mathbf{A}^T\mathbf{S}\mathbf{A}\mathbf{B}(\mathbf{R} + \mathbf{B}^T\mathbf{S}\mathbf{B})^{-1}\,\mathbf{B}^T\mathbf{S}\mathbf{A} \tag{15}$$

Thus, the control input u_k can be calculated from the control law (12) as:

$$\mathbf{u}_k = \mathbf{u}^* - \mathbf{K}(\mathbf{x}_k - \mathbf{x}^*) \tag{16}$$

However, when state variables are not directly available for control, an observer must be built to estimate the state variables from the input and output variables of the system. The most widely known optimal observer is the Kalman filter, which can be readily applied to linear models with additive Gaussian noises, such as the one under study. The algorithm of the Kalman filter is presented below in tables 1 and 2, as applied to the state estimation problem given by Eqs. (5) and (6) [13, 14, 15]:

Table 1 – Discrete time evolution update equations

$$\boldsymbol{x}_k^- = \boldsymbol{A}_k\boldsymbol{x}_{k-1} + \boldsymbol{B}_k\boldsymbol{u}_{k-1} \tag{17.a}$$

$$\mathbf{P}_k^- = \mathbf{A}_k\,\mathbf{P}_{k-1}\mathbf{A}_K^T + \mathbf{F}_k \tag{17.b}$$

Table 2 – Measurement update equations

$$\mathbf{K}_k = \mathbf{P}_k^-\,\mathbf{C}_k^T\left(\mathbf{C}_k\,\mathbf{P}_k^-\,\mathbf{C}_k^T + \mathbf{G}_k\right)^{-1} \tag{17.c}$$

$$\mathbf{x}_k = \mathbf{x}_k^- + \mathbf{K}_k\left(\mathbf{z}_k - \mathbf{C}_k\mathbf{x}_k^-\right) \tag{17.d}$$

$$\mathbf{P}_k = \left(\mathbf{I} - \mathbf{K}_k\,\mathbf{C}_k\right)\mathbf{P}_k^- \tag{17.e}$$

where $\mathbf{K}_k$ is Kalman's gain matrix and $\mathbf{P}_k$ is the covariance matrix of the estimated state variables.

5 RESULTS AND DISCUSSIONS

In order to examine a test case involving typical conditions resulting from a shut-down in the flow through the pipeline, a hypothetical situation was simulated where the stagnant fluid was assumed to be initially at the uniform temperature of 65°C in a circular domain with external diameter of 0.1682 m (6”). The thermophysical properties were assumed constant and given by k = 12.54 W m^{-1} °C^{-1}, ρ = 933.59 kg m^{-3} and c_p = 1826.80 J kg^{-1} °C^{-1}. The objective of the heating system was to drive the stagnant fluid temperature to a reference value of 30°C. The heating system was turned on when the lowest predicted temperature in the domain reached the critical value of formation of solid deposits, which was assumed to be 20 °C. For the results presented below, the Biot number was taken as 1.

For the prediction of the state variables, one single sensor was considered available, located at the surface of the circular domain. Figure 2 presents the simulated measured temperatures, both during the cooling and heating periods. The simulated measurements contained Gaussian errors with a constant standard deviation of 3°C.

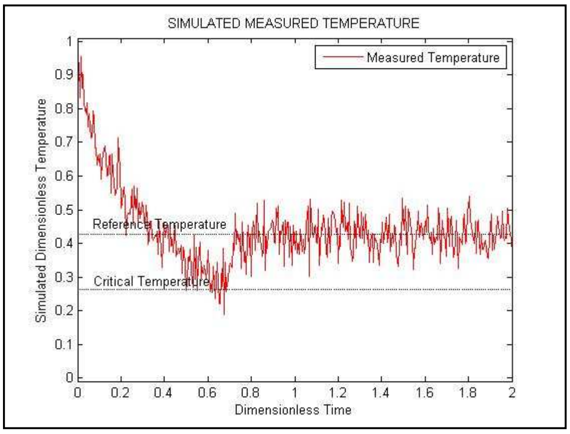
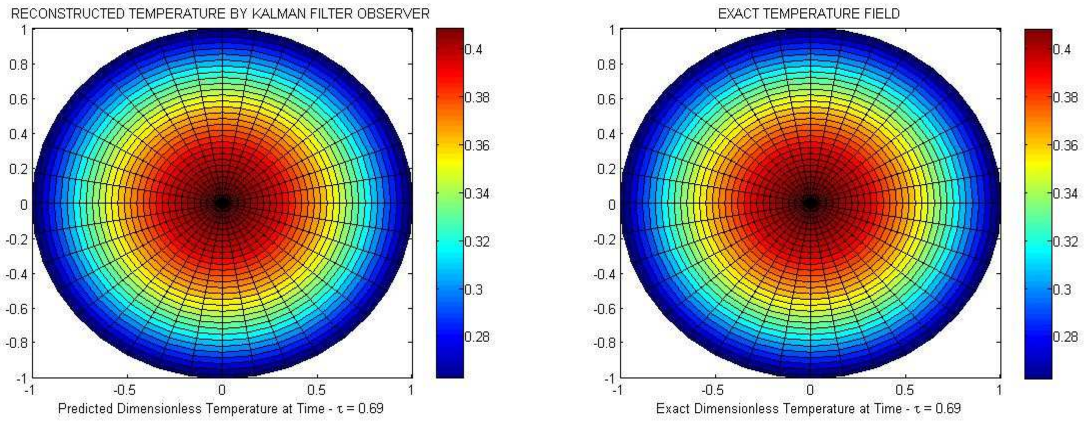


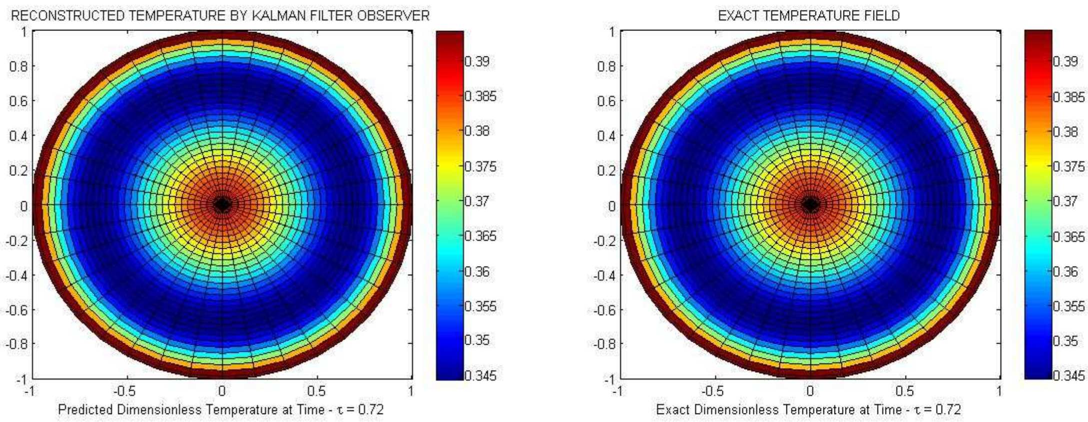
Figure 2: Measured temperature on the external surface

The Kalman filter was used to estimate the overall fluid temperature field in the domain, from the simulated noisy measurements shown in figure 2. Figures 3-5 present a comparison between the predicted and the exact temperature fields, for dimensionless times of τ = 0.69, 0.72 and 1.1, respectively. Figures 3-5 clearly reveal an excellent agreement between exact and predicted temperatures, even for the large standard deviation of the observation errors of 3°C.



(a) (b)

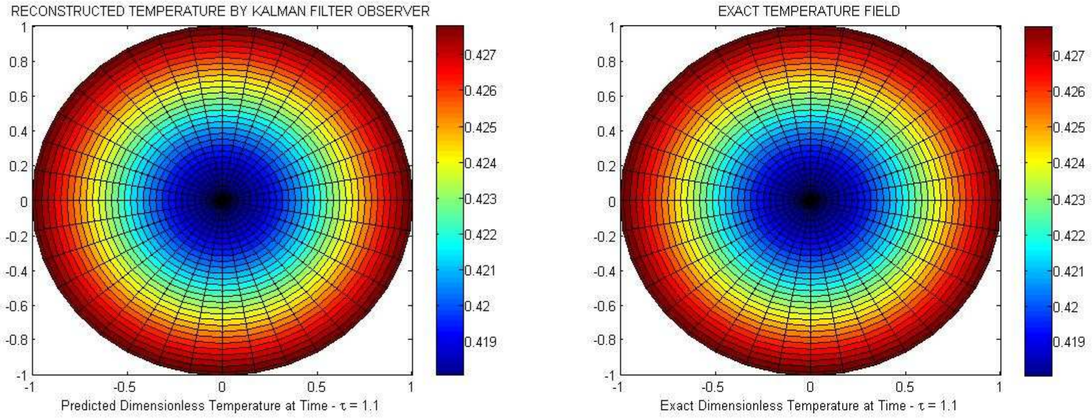
Figure 3: Comparison between (a) predicted temperature distribution and (b) exact temperature distribution for τ = 0.69



(a) (b)

Figure 4: Comparison between (a) predicted temperature distribution and (b) exact temperature distribution

for $\tau = 0.72$



(a) (b)

Figure 5: Comparison between (a) predicted temperature distribution and (b) exact temperature distribution for $\tau = 1.1$

The temperatures predicted by the Kalman filter in the whole domain were used in the control strategy described above. The control strategy was applied with the weighting matrices **Q** = **R** = **I** (identity matrix). Figure 6 shows the time evolution of the predicted temperatures at two positions in the domain (R = 0 and R = 1). One can clearly see that the heating is turned on when the lowest temperature in the domain (at R = 1) reaches the critical value. Then, the temperatures at these two positions gradually approach the reference value through the action of the control system on the boundary heat flux. The optimal heat flux obtained through the control strategy described above is presented in figure 7. This figure shows that the heat flux attains large values when the heating is turned on, but gradually tends to a constant value that provides a uniform temperature in the medium within the time range of interest.

A comparison of figures 2 and 6 shows the effect of the Kalman filter on the temperature at the position R = 1. It is also important to note that a completely erratic heat flux would be obtained if the measurements shown in figure 2 were directly used in the control approach.

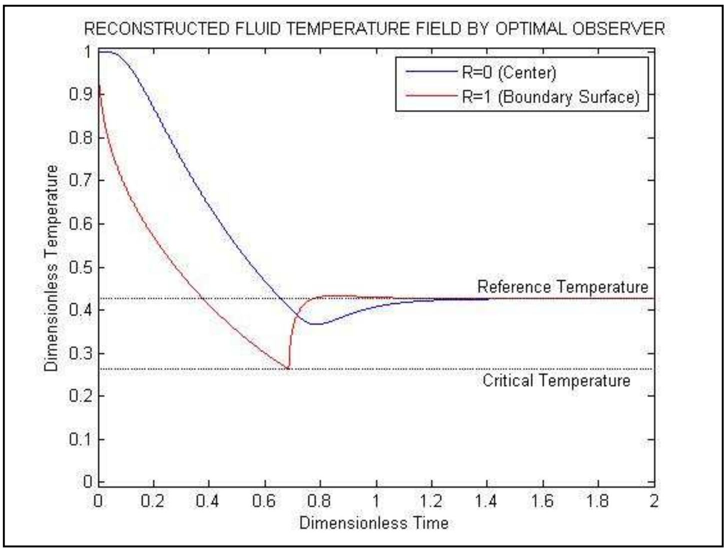


Figure 6: Evolution of the predicted temperatures with the action of the optimal control

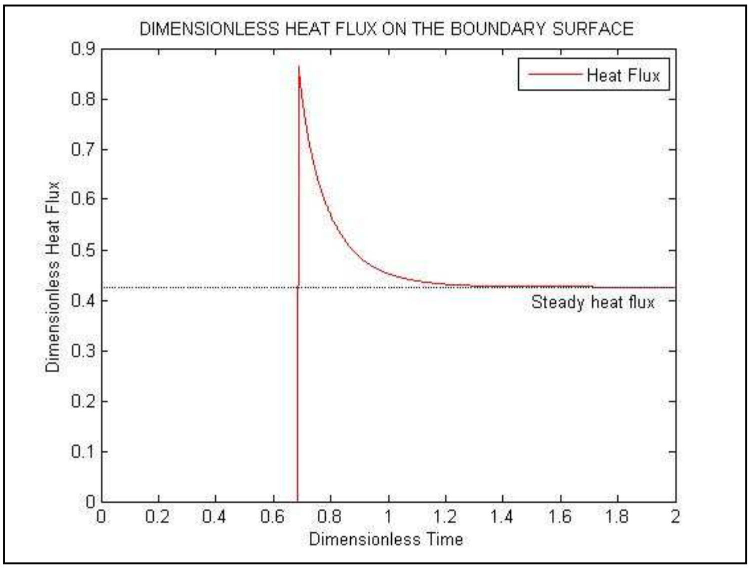


Figure 7: Optimal heat flux on the boundary surface

6 CONCLUSIONS

The objective of this paper was to apply an optimal control strategy to a heating system, in order to avoid the formation of solid deposits in pipelines. The optimal control input was determined with a linear quadratic regulator, where a quadratic cost functional was minimized through the solution Riccati's equation. Predicted temperatures in the whole domain, obtained with the Kalman filter, were used in the control strategy instead of the direct measurements. The Kalman filter was capable of providing accurate estimates for the temperature field in the region, even for large errors in the observation model. With the present approach, the control strategy could be effectively applied and the temperature in the region was maintained above the critical one during the time range of interest.

7 ACKNOWLEDGEMENTS

The authors would like to thank Petrobras and the Brazilian agencies for the fostering of science, CNPq, CAPES and FAPERJ, for sponsoring this work.

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