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An autonomous approach for driving systems towards their limit: an intelligent adaptive anti-slug control system for production maximization

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Abstract: Anti-slug control in multiphase risers involves stabilizing an open-loop unstable operating point. Existing anti-slug control systems are not robust and tend to become unstable after some time, because of inflow disturbances or plant dynamic changes, thus, requiring constant supervision and retuning. A second problem is the fact that the ideal setpoint is unknown and we could easily choose a suboptimal or infeasible operating point. In this paper we present a method to tackle these problems. Our complete control solution is composed of an autonomous supervisor that seeks to maximize production by manipulating a pressure setpoint and a robust adaptive controller that is able to quickly identify and adapt to changes in the plant. The supervisor is able to automatically detect instability problems in the control loop and moves the system to a safer, stable operating point. Our proposed solution has been tested in a experimental rig and the results are very encouraging.

Keywords: Anti-slug control, adaptive control, autonomous control systems, production maximization

1. INTRODUCTION

The severe-slugging flow regime which is common at offshore oilfields is characterized by large oscillatory variations in pressure and flow rates. This multi-phase flow regime in pipelines and risers is undesirable and an effective solution is needed to suppress it (Godhavn et al., 2005). One way to prevent this behaviour is to reduce the opening of the top-side choke valve. However, this conventional solution reduces the production rate from the oil wells. The recommended solution to maintain a non-oscillatory flow regime together with the maximum possible production rate is active control of the topside choke valve (Havre et al., 2000). Measurements such as pressure, flow rate or fluid density are used as the controlled variables and the topside choke valve is the main manipulated variable.

From an economic point of view, we would like to have the lowest possible pressure (maximum valve opening) in the pipeline/riser system. This translates into low pressures at the bottom hole of the wells which maximizes the fluid inflow from the reservoir. However, as the pressure setpoint decreases the stabilization of the system becomes more difficult and, thus, the choice of the ideal setpoint is hard task. In fact, the ideal pressure setpoint is unknown and varies with the inflow conditions. Setting it too high reduces the production. Setting it too low may be infeasible (uncontrollable), leading to slug flow. Consequently, constant monitoring of the control system by the operators is needed.

Hence, we propose an autonomous supervisory system that safely drives the process in the direction of minimum pressure for production maximization. The main idea is to gradually decrease the pressure setpoint until just before the control performance is no longer acceptable due to slugging. The supervisor automatically assesses the performance and stability of the control loop and decides the direction in which we should change the pressure setpoint in order to ensure stable operation. For example, if we detect slow oscillations with growing amplitude in the output, the setpoint should be increased since it is safer and easier to stabilize.

Nonetheless, the standard linear controllers are typically designed for a given operating point and they may fail to give acceptable performance when the setpoint changes considerably. Another problem are the disturbances in the inflow, which greatly affect the dynamics of the plant.

For these reasons we implemented a robust adaptive anti-slug controller. For our application we chose the robust-adaptive output feedback control design method proposed by Lavretsky (2012). This method falls into the model-reference adaptive control category (Lavretsky and Wise, 2013) and fits well in our approach. This controller is able to quickly identify and adapt to changes in the plant dynamics in order to recover the desired performance.

Our complete control solution is composed of the autonomous supervisor and the robust adaptive slug control. It turns out the combination of these two elements results in a great synergy: the periodic setpoint changes triggered by the supervisor gives enough excitement in the system

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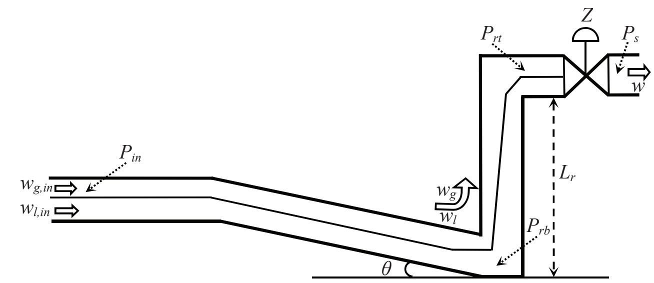

Fig. 1. Schematic representation of system

for the adaptation to work well; a well functioning adaptive controller allows the supervisor to push the system closer to the limit for a wide range of operating conditions.

Its worth to point out that this approach is very general and can be applied in a variety of applications with similar characteristics: dynamics change when approaching the (possibly unknown) operating limit of the system.

This paper is organized as follows. Section 2 describes the pipeline-riser system. The general approach that we proposed is described in Section 3, where Details about the supervisor and the adaptive controller are found. The results are presented in Section 4. Finally, we summarize the main conclusions and remarks in Section 5.

2. SYSTEMS DESCRIPTION

Fig. 1 shows a schematic presentation of the system. The inflow rates of gas and liquid to the system, $w_{g,in}$ and $w_{l,in}$, are assumed to be independent disturbances and the top-side choke valve opening ($0 < Z < 100\%$) is the manipulated variable. A fourth-order dynamic model for this system was presented by Jahanshahi and Skogestad (2011). The state variables of this model are as:

- m_{gp}: mass of gas in pipeline [kg]
- m_{lp}: mass of liquid in pipeline [kg]
- m_{gr}: mass of gas in riser [kg]
- m_{lr}: mass of liquid in riser [kg]

The four state equations of the model are

$$\dot{m}_{gp} = w_{g,in} - w_g \tag{1}$$

$$\dot{m}_{lp} = w_{l,in} - w_l \tag{2}$$

$$\dot{m}_{gr} = w_g - \alpha w \tag{3}$$

$$\dot{m}_{lr} = w_l - (1-\alpha) w \tag{4}$$

The flow rates of gas and liquid from the pipeline to the riser, w_g and w_l, are determined by pressure drop across the riser-base where they are described by virtual valve equations. The outlet mixture flow rate, w, is determined by the opening percentage of the top-side choke valve, Z. The different flow rates and the gas mass fraction, α, in the equations (1)-(4) are given by additional model equations given by Jahanshahi and Skogestad (2011). In this paper we used the linearized version of this model for the control design methods. Alternatively, empirical low-order models could have been used (Jahanshahi and Skogestad, 2013).

3. AN AUTONOMOUS APPROACH FOR DRIVING SYSTEMS TOWARDS THEIR LIMIT

Here we propose an autonomous control system to drive a process towards its operational limit. Our solution is composed of two main elements:

- supervisory system that overlooks the control loop, assess stability and performance and makes a decision on which direction (increase or decrease) the setpoint should move. In our application, the strategy is to gradually reduce the pressure setpoint until a stability problem is detected (e.g., slow oscillations start to build-up). At this point the supervisor should move the system to a safer operating point (increase setpoint).
- a robust adaptive controller that regulates the system to the setpoint specified by the supervisory controller. The controller must be able to identify changes in the plant dynamics and compensate for it to give acceptable closed-loop performance in a wide range of operating conditions.

We believe that the combination of frequent setpoint changes by the supervisor with and adaptive control scheme can be very fruitful because the periodic setpoint changes triggered by the supervisor gives enough excitement in the system for the adaptation to work well; a well functioning adaptive controller allows the supervisor to push the system closer to the limit compared to linear controllers.

3.1 Supervisory control

A key component in an autonomous supervisor is the ability to quickly detect problems in the control loop. In our application the main problem is the appearance of slugging flow which is characterized by growing (slow) oscillations in the pressures and flows with a certain frequency. Such oscillations are a signal that the controller is having problems to control the process at the given operating conditions and should move to a safer setpoint. Algorithm 1 exemplifies a basic supervisory scheme for the anti-slug control problem. P_{sp} is the pressure setpoint and ΔP_{sp} represents the size of the steps. The pressure can be measured at any point of the system (e.g. riser base or riser top). Note that the amplitude of the step when increasing or decreasing the setpoint may be different.

The basic idea is to periodically check for slow oscillations in the system and decrease the setpoint only if nothing is detected. On the other hand, we should quickly increase the setpoint if the amplitude of the oscillations are starting to grow. In this case, it could be desirable to reset the adaptation parameters to the previous good values using, for instance, a look-up table.

For a practical application, however, many other safeguards must be included. For example, if a major disturbance occurs, the controlled variable may drift away from the setpoint very rapidly and the oscillation detection system may fail to perceive in time. In order to quickly detect these major problems a second, independent check function must be implemented. In our case we periodically analyse the mean control error over a short time horizon.

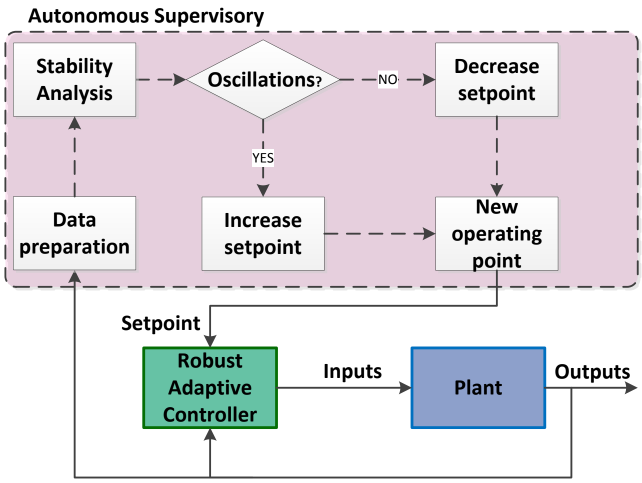

Fig. 2. Simplified representation of the supervisory system

A warning flag is raised if the mean error is increasing too quickly or if it crosses some large threshold. We must also include a routine to detect high frequency oscillations generally caused by having too high control gains for the given operating conditions. In this case we should decrease the setpoint instead. Other functions of the supervisor could include looking after the adaptive control (e.g. we may want to turn off the adaptation during the starting up period), fault detection, alarms, etc.

Algorithm 1 A simplified supervisory system algorithm

loop
  analyse measured data

  if slow oscillations detected **then**

    if amplitude is increasing **then**
      $P_{sp} \leftarrow P_{sp} + \Delta P_{sp,1}$
      return to previous adaptation values
    else
      wait longer
    end if

  else
    $P_{sp} \leftarrow P_{sp} - \Delta P_{sp,2}$
  end if
end loop

Oscillation detection system A key component in an autonomous supervisor is the ability to quickly detect slow oscillations in the closed-loop system. This can be achieved by periodically applying a frequency analysis tool in the measured data (e.g. pressures) in a moving-horizon manner. Our chosen approach is to estimate the power spectral density using a fast Fourier transform and then check if the main frequency component of the signal lies in a neighbourhood of the slug frequency. If this is the case, a warning flag is raised. The same frequency analysis can be used to estimate the amplitude of the oscillation, allowing us to tell whether the oscillations are increasing or fading out.

Our practical experience has shown that this approach is quite robust and it only requires knowledge of the slug frequency for the specific application. No other tuning parameters are necessary.

3.2 Robust Adaptive Control Design

We implemented the robust adaptive output feedback design method proposed by Lavretsky (2012). This method falls into the model-reference adaptive control category (Lavretsky and Wise, 2013). The main components of this controller are: an observer-like reference model which specifies the desired closed-lop response; a linear baseline controller that gives the desired performance and robustness at nominal conditions; the adaptation law which augments the input in order to recover the desired performance despite the disturbances and uncertainties (See Fig. 3). For completeness, we will outline in the following the design method that was used. We follow the notation of Lavretsky and Wise (2013).

We assume that system can be described in the following form

$$\begin{aligned} \dot{x} &= Ax + B\Lambda(u + \Theta^T\Phi(x)) + B_{sp}z_{sp} \\ y &= Cx, \qquad z = C_z x \end{aligned} \tag{5}$$

where $A \in R^{n\times n}$, $B \in R^{n\times m}$, $C \in R^{p\times n}$ and $C_z \in R^{m\times n}$ are known matrices. Note that the matrices may have been augmented to include the integral feedback connections. The vector $x \in R^n$ represents the system states, $y \in R^p$ are the available measurements, $u \in R^m$ are the inputs and $z \in R^m$ are the variables we wish to regulate to given setpoints z_{sp}. The uncertainties are described by an unknown diagonal matrix Λ, an unknown matrix of coefficients Θ and a known Lipschitz-continuous regressor $\Phi(x)$. We assume that the number of available measurements p is larger than the number of control inputs m. In this case, the system can be 'squared-up' using pseudo-control signals to yield minimum-phase plant dynamics.

Representation (5) fits well with our application. One of the main challenges is the very large process gain variation as we change the pressure setpoint. This can be represented by Λ. Furthermore, the poles and zeros of the linearized dynamics move considerably as the pressure reduces. This effect can be modelled by the term $\Theta^T\Phi(x)$ as long as we make a good choice for the regressor $\Phi(x)$.

The first step is to design a reference model with the desired closed-loop dynamics. In this case we compute an optimal state feedback K_{LQR} by employing the LQR method such that

$$A_{ref} = A - BK_{LQR} \tag{6}$$

as the desired dynamic characteristics. It has been shown (Lavretsky, 2012) that the transient dynamics of the adaptation scheme can be improved by using an observer-like model reference. Thus, our reference model becomes

$$\begin{aligned} \dot{x}_{ref} &= A_{ref}x_{ref} + L_v(y - y_{ref}) + B_{sp}z_{sp} \\ z_{ref} &= C_z x_{ref} \end{aligned} \tag{7}$$

where $L_v \in R^{n\times m}$ is the prediction error feedback gain that is obtained by solving a certain algebraic Riccati equation (Lavretsky, 2012). The 'square-up' step of the plant dynamics should be performed prior to the design of L_v.

Our chosen implementation approach is to augment a baseline linear controller with the adaptor instead of using a fully adaptive control. The reasoning comes from the fact that in most realistic applications a stabilizing baseline controller might already be in place. This baseline controller would have been designed to give satisfactory performance under nominal conditions around an operating point. If the performance degrades due to changes of operating conditions, we will attempt to recover the desired performance by augmenting the baseline controller with an adaptive element. The total control input is the sum of the components

$$u = u_{bl} + u_{ad} \tag{8}$$

where u_{bl} denotes the baseline control input and u_{ad} is the adaptive augmentation control signal.

The adaptation increment u_{ad} is given by

$$u_{ad} = -\hat{K}_u u_{bl} - \hat{\Theta}^T \Phi(x_{ref}) \tag{9}$$

where $\hat{\Theta}$ is an estimation of Θ and $\hat{K}_u$ serves as an estimate of $(I_{m\times m} - \Lambda^{-1})$.

Given the adaptation rates Γ_Θ and Γ_u, the adaptive law with the Projector Modification (Pomet and Praly, 1992) can be written as

$$\frac{d\hat{\Theta}}{dt} = Proj(\hat{\Theta}, -\Gamma_\Theta \Phi(x_{ref}) e_y^T R_0^{-0.5} W S^T) \tag{10}$$

$$\frac{d\hat{K}_u}{dt} = Proj(\hat{K}_u, -\Gamma_u u_{bl} e_y^T R_0^{-0.5} W S^T) \tag{11}$$

where

$$e_y = y_{ref} - y \tag{12}$$

is the output tracking error and the matrices R_0, W and S are selected to ensure that the tracking error e_y becomes small in finite time.

The projector operator $Proj$ ensures that the adaptive parameters always lie inside a user-defined region and can never diverge. The robustness of this adaptive law can be improved by including a dead-zone modification that stops adaptation when the error e_y is too small. Such modification ensures that the adaptation parameters will not drift because of measurement noise (Lavretsky and Wise, 2013).

Remark 1. It is interesting to note that upon combining (9) and (8) we get

$$u = (1 - \hat{K}_u) u_{bl} - \hat{\Theta}^T \phi(x_{ref}) \tag{13}$$

where we see that the adaptor is in essence modifying the baseline controller gain by a factor $(1 - \hat{K}_u)$. The second term in the right-hand side of the equation tries to match and cancel the effect of the nonlinear uncertainties in (5).

Remark 2. The observer-based model reference (7) works as a robust closed-loop Luenberger estimator when we select the baseline controller

$$u_{bl} = -K_{LQR} x_{ref} \tag{14}$$

This leads to an output feedback controller equivalent to the loop transfer recovery using the Lavretsky method, which has been proven to have excellent robustness properties (Lavretsky and Wise, 2013). In our application, (14) was our baseline controller of choice because of its robustness properties and its good performance observed in our experiments. Nonetheless, any other linear controller (e.g PI control) could have been selected for the baseline layer. In fact, our experiments have shown that the adaptive control scheme presented above is able to recover the desired performance even if a poorly tuned PI controller is used in the baseline (See Figures 11 and 12).

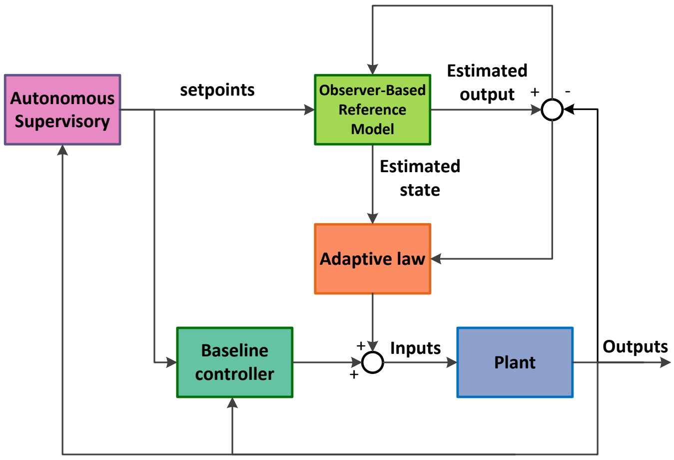

Fig. 3. Simplified block diagram of the proposed adaptive control scheme

Remark 3. Another advantage of using the augmentation approach for the adaptive scheme (rather than fully adaptive control) is that the adaptation could be turned off when necessary without loosing control of the system. This can be particularly important in some situations such as start-up.

4. RESULTS

4.1 Experimental setup

The experiments were performed on a laboratory setup for anti-slug control at the Chemical Engineering Department of NTNU. Fig. 4 shows a schematic presentation of the laboratory setup. The pipeline and the riser are made from flexible pipes with 2 cm inner diameter. The length of the pipeline is 4 m, and it is inclined with a 15° angle at the bottom of the riser. The height of the riser is 3 m. A buffer tank is used to simulate the effect of a long pipe with the same volume, such that the total resulting length of pipe would be about 70 m.

The topside choke valve is used as the input for control. The separator pressure after the topside choke valve is nominally constant at atmospheric pressure. The nominal feed into the pipeline is assumed to be at flow rates 4 l/min of water and 4.5 l/min of air. With these boundary conditions, the critical valve opening where the system switches from stable (non-slug) to oscillatory (slug) flow is at $Z^* = 15\%$ for the top-side valve. The bifurcation diagrams are shown in Fig. 5.

The desired steady-state (dashed middle line) in slugging conditions ($Z > 15\%$) is unstable, but it can be stabilized by using control. The slope of the steady-state line (in the middle) is the static gain of the system,

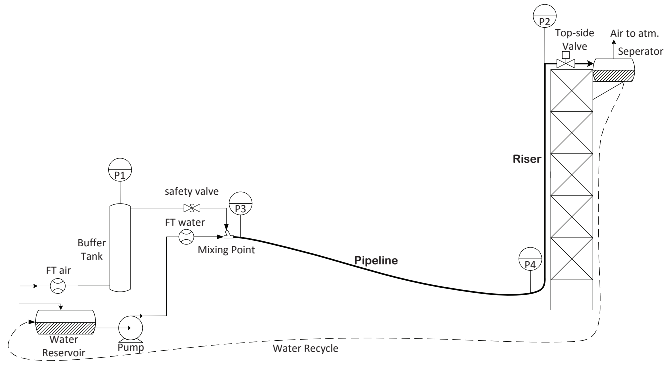

Fig. 4. Experimental setup

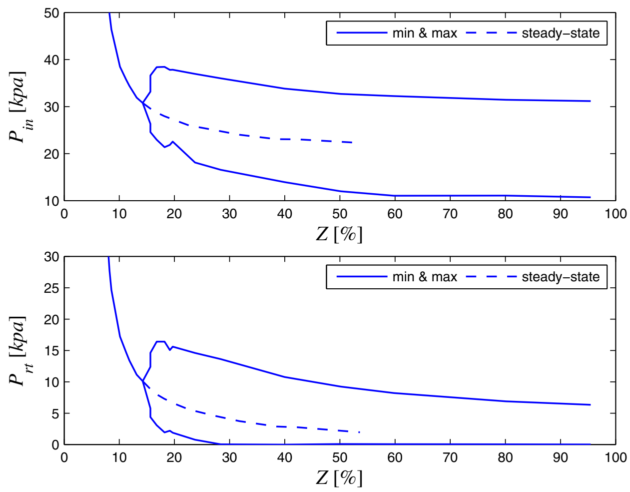

Fig. 5. Bifurcation diagrams for experimental setup

$k = \partial y/\partial u = \partial P_{in}/\partial Z$. As the valve opening increase this slope decreases, and the gain finally approaches to zero. This makes control of the system with large valve openings very difficult.

4.2 Supervisory control

The main parameter for the implementation of the supervisory controller is the period of the slug oscillation. This variable depends mainly on the dimensions of the pipeline and riser, although the operating conditions (e.g. valve opening) do have some effect on it. For our purposes it is enough to have an estimation of the order of magnitude of the frequency of the oscillations. In our application we observed variations in the oscillation period ranging from 40 to 70 seconds. Thus, any oscillation in this frequency range will be reported by the oscillation detection algorithm. The core idea of our supervisor is Algorithm 1. The loop was executed every 20 seconds to avoid strong interactions with the stabilizing control layer. The length of the horizon for analyses in the oscillation detector was set to 90 seconds to ensure that a full slug cycle would be detected.

4.3 Adaptive Controller

We designed our controllers based on the linearized version of the model described on Section 2 for a valve opening $Z = 30\%$. In the control algorithm we consider measurements of both the inlet pressure of the pipeline (P_{in}) and the pressure in the riser top (P_{rt}). The regulated output in experiments is $z = P_{in}$. The second measurement is used to ensure robustness properties of the LTR baseline and the adaptive controllers.

In our application we chose (14) as our baseline controller because of its excellent robustness properties and its good performance observed in our experiments. Prior to conducting the LQG/LTR controller design, we augmented the plant dynamics to include the integrated inlet pressure tracking error $e = P_{sp} - P_{in}$.

For the adaptive algorithm we chose as basis function Φ the linear relationship

$$\Phi(x_{ref}) = C_z x_{ref} \equiv \hat{P}_{in} \tag{15}$$

where $\hat{P}_{in}$ is an estimation of the inlet pressure. From our analysis this simple basis function is enough to describe the variation in the plant dynamics (zeros and poles) due to changes in the operating point (indicated by P_{in}). The gain uncertainty is described by the unknown scalar parameter Λ. Therefore, our adaptation scheme is composed of two scalar adaptive parameters only. The Projector Operator ensures that these parameters are bounded and remain inside the interval $[-5,\ 5]$.

To improve the quality of our adaptation and to ensure the overall robustness of the system, we switched on the adaptation only after a setpoint change is made and for a limited amount of time (e.g. for 1 min). This prevents the system to wrongly adapt to the disturbances. When the supervisory layer detects a problem in the system and the setpoint is increased, the adaptation parameters are reset to the closest previously computed value for the given setpoint using a lookup table.

For comparison we have also implemented a PI controller in the baseline layer. Our experiments have shown that the adaptive control scheme presented in the previous section is able to recover the desired performance even if a poorly tuned PI controller is used in the baseline (See Figures 11 and 12).

4.4 Experimental results: nominal flow conditions

In this experiment the feed into the pipeline is set to be at constant flow rates, 4 l/min of water and 4.5 l/min of air. Figures 6 depict the results for a 48 minutes run of the complete system. The setpoint is indicated by the red solid line in the top plot. Note that the setpoint is only decreased when the supervisor is sure it is safe. The detection of growing oscillations is indicated by the red flag. In Fig. 6 these can be seen around the times 15.5, 27, 34 and 42 minutes. The supervisor is able to safely keep the system at stable conditions at fairly high valve openings. Figure 7 shows the adaptation parameter for the same experiment. The adaptation is switched on after 100 seconds to avoid the start-up dynamics. Its interesting to note that at first the parameter $\hat{K}_u$ increases (the gain $(1-\hat{K}_u)$ decreases) indicating that initially the controller is a bit too aggressive for the given conditions. However, as the supervisor reduces the setpoint for P_{in} the parameter $\hat{K}_u$ decreases (the gain $(1-\hat{K}_u)$ increases) considerably to maintain the desired performance. Note that we reset the

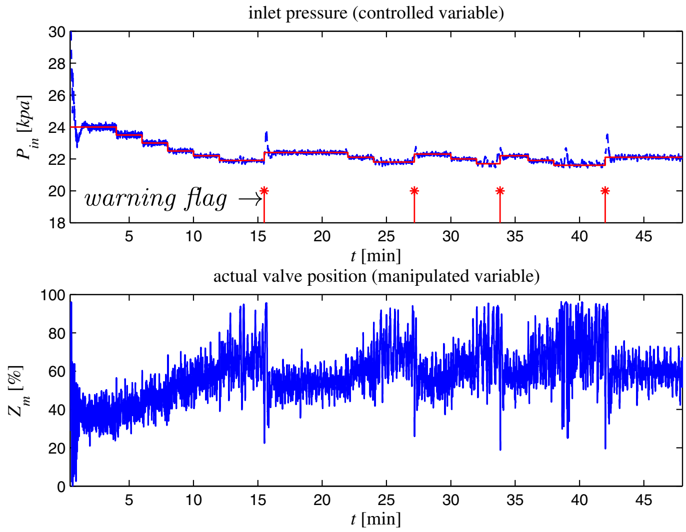

Fig. 6. Experiment 1 : supervisory control and a well tuned LTR baseline controller: adaptation is ON

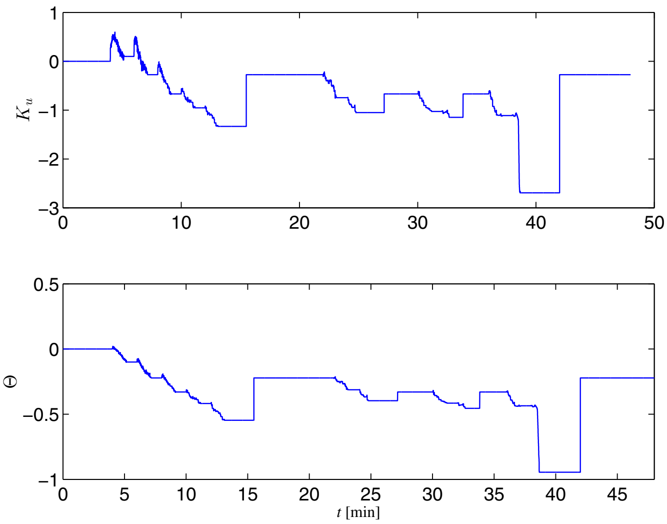

Fig. 7. Experiment 1: adaptive parameters

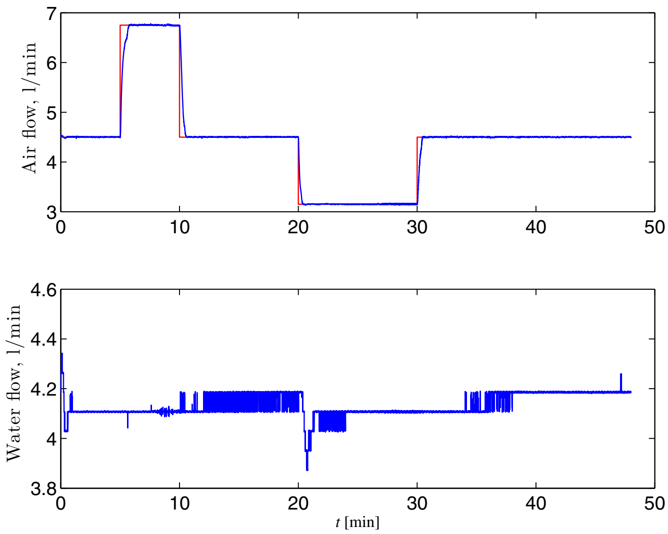

Fig. 8. Experiment 2: major disturbance in the inlet flow rates

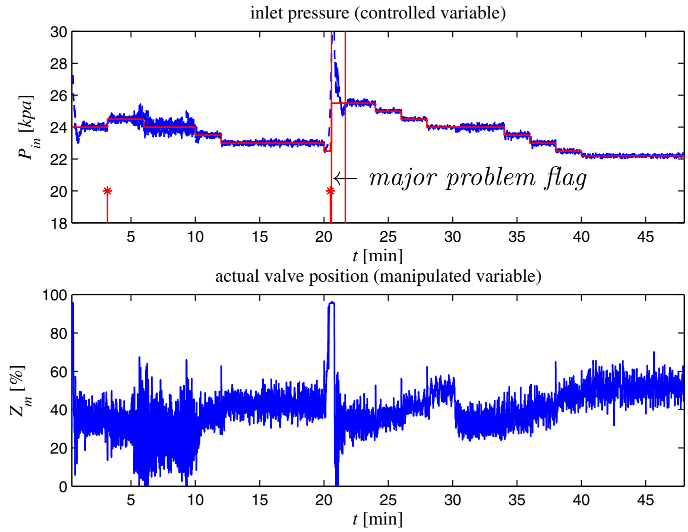

Fig. 9. Experiment 2: major disturbance in the inlet flow rates. LTR baseline controller: adaptation is ON

adaptation parameters when a problem is detected (red flag).

4.5 Experimental results: large change of operating conditions

In this set of experiments we tested the more realistic and challenging conditions in which the gas to liquid ratio varies considerably throughout the experiment. Initially the feed into the pipeline is set to constant flow rates 4 l/min of water and 4.5 l/min of air. Then, a sequence of steps in the air flow is applied: first we increase the air flow by 50% at $t = 5$ min followed by a 30% decrease at $t = 20$ min (see Fig. 8). Changes in the air flow and pressures naturally perturb the water flow. Note that these changes represent very serious disturbances that have big effect in the dynamics of the plant.

Figure 9 depicts the performance of the control system. The more serious disturbance here is when the air flow decreases ($t = 20$ min). The pressure rapidly diverges since it became very difficult to stabilize the system at these conditions. Nonetheless, the supervisory layer quickly detected the problem and immediately moved the system to a safer operating point. After stabilizing the process, the robust adaptive controller was able to adapt its parameters for the new dynamics (see Fig. 10), making it possible to reduce the pressure setpoint even under such harsh conditions. It is worth to point out that slugging flow did not occur at any moment and the good performance of the controller remained consistent, proving the great resilience of our proposed solution. Such a result would not have been possible to achieve without an autonomous supervisor and an adaptive controller.

4.6 Experimental results: using a poor baseline controller and nominal flow conditions

For comparison, it is interesting to investigate the effect of the baseline controller in the overall performance of the control system. The incentive for doing so is clear: in most realistic applications a stabilizing baseline controller might

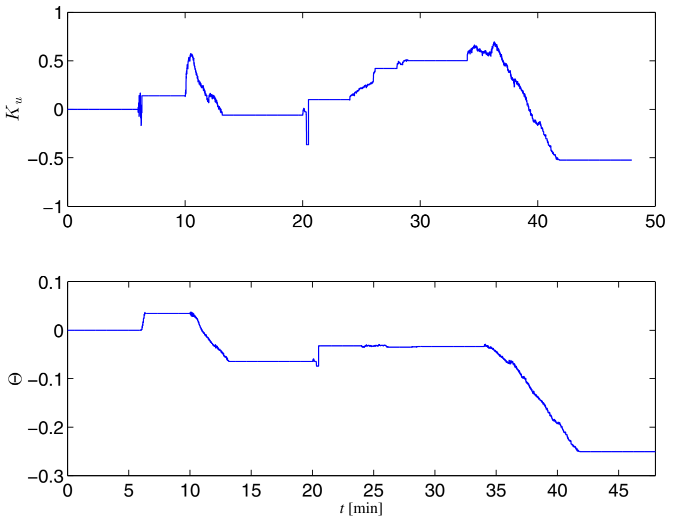

Fig. 10. Experiment 2: adaptive parameters when using the LTR controller

already be in place and perhaps we do not want to change it.

For this purpose we consider as the baseline a poorly tuned PI controller. Figure 11 shows the results of the autonomous supervisor with the PI controller without any adaptation. We observe an overall poor performance and the inability to operate with large valve openings.

The experiment was repeated with the same PI controller but now the adaptation was switched on. The same reference model used in experiments 1 and 3 is employed here. Figure 12 depicts the results. Surprisingly, the closed-loop performance was greatly improved compared to Fig. 11 and we are able to operate at a larger valve opening. For a complete comparison, we ran the same experiment using our well tuned LTR controller (14) and the adaptation switched on. Figure 13 shows the result of this controller where we observe good tracking performance throughout the experiment.

Table 1 summarizes the results of the three experiments where we compare the tracking performance based on the integrated square error (ISE) and the 'economic' performance based on the mean valve opening and pressure. Note that the improvement from experiment 3 to 4 is substantial, where we observe an increase of 31% of the average valve opening. On the other hand, the improvement from experiment 4 to 5 is only minor. Nevertheless, our recommendation is to always use a good robust controller in the baseline. This will ensure safer operation during start-up (when the adaptation is likely to be turned off) or during reset of the control system.

It is important to point out that the adaptive controller we implemented relies on the measurement of both top and bottom riser pressure. It would be interesting to investigate the performance of this adaptive law for the case when only one of the measurements is available.

5. CONCLUSION

In this paper we proposed an autonomous control system that seeks to maximize oil production in off-shore

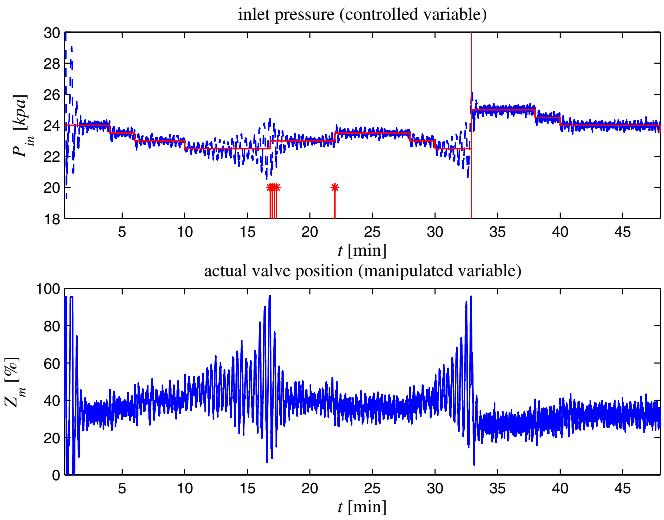

Fig. 11. Experiment 3: supervisor control and a poorly tuned PI control as the baseline: adaptation is OFF

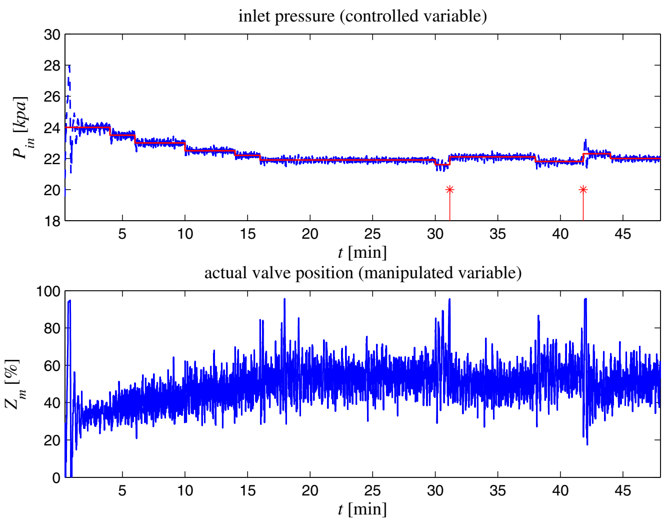

Fig. 12. Experiment 4: supervisory control and a poorly tuned PI baseline controlerl: adaptation is ON

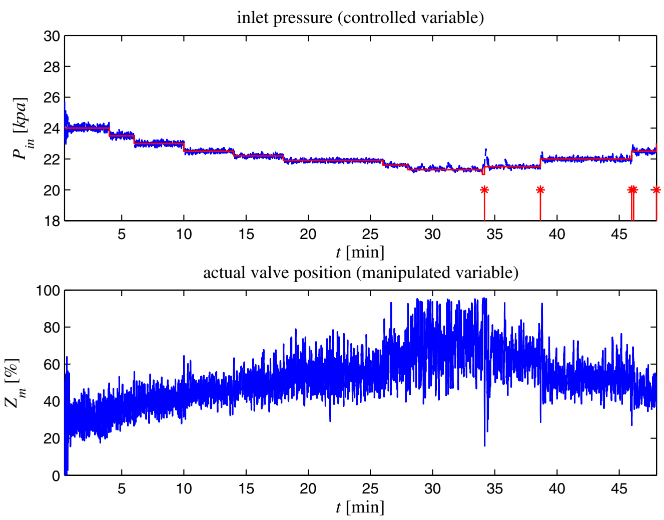

Fig. 13. Experiment 5: supervisory control and a LTR baseline controller: adaptation is ON

Table 1. Comparison of different controllers with same experimantal conditions

Experiment	Controller	ISE	Mean valve opening (%)	Mean pressure(kpa)
3	Bad PI - adaptation OFF	6.2	38.45	23.58
4	Bad PI - adaptation ON	0.76	50.42	22.33
5	LTR - adaptation ON	0.64	53.23	22.29

oilfields. Our complete control solution is composed of an autonomous supervisor that manipulates the pressure setpoint and a robust adaptive controller that is able to quickly identify and adapt to changes in the plant. The supervisor was also able to automatically detect instability problems in the control loop and moved the system to a safer operating point when necessary. The experimental results are very encouraging. The method demonstrated great resilience and good performance in a variety of operating conditions. Our solution will lessen the demand for manual supervision, will reduce the need for frequent retuning of the controller and will maximize the oil production.

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