Adoptive Control of Well Drilling Systems

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Abstract

Control of well drilling operations poses a challenging issue to be tackled. The loss of well control could lead to the occurrence of blowout as a severe threat, involving the risk of human lives and environmental and economic consequences. Conventional proportional-integral (PI) controller is a common practice in the well control operation. The small existing margin between pore pressure and fracture gradients jeopardizes the efficiency of this conventional method to exercise an accurate and precise pressure control. There is a significant incentive to develop more efficient control methodologies to precisely control the annular pressure profile throughout the well bore to ascertain the down-hole pressure environment limits. Adaptive control presents an attractive candidate approach to achieving these demanding goals through adjusting itself to the changes during well drilling operations. The current paper presents a set of adaptive control paradigms in the form of self-tuning control (STC). The developed STC's are comparatively evaluated on a simulated well drilling benchmark case study for both regulatory and servo-tracking control objectives. The different sets of test scenarios are conducted to represent the superior performance of the developed STC methods compared to the conventional PI control approach.

Keywords: Adaptive Control, Self-tuning Control, Well Drilling System

1. Introduction

The oil and gas industry is increasingly facing more challenging drilling operations in which proper well control is of great importance. The loss of well control may lead to blowout, representing one of the most severe threats which involves the risk of human lives and environmental and economic consequences. A fluid circulation system is used to maintain the pressure profile along the well during well operation. The drill fluid, usually called mud, is pumped into the drill string, flows down the drill bit, sprays out through the bit, circulates back up the annulus, and finally exits through a choke valve. The small margin between pore pressure and fracture gradients is the root of these challenging problems, demanding for accurate and precise pressure control (Salahshoor et al., 2012). If the bottom-hole pressure becomes too low (i.e., below the pore pressure), there could be influx from the reservoir, which can lead to an uncontrolled blowout. If the bottom-hole pressure profile becomes too high (i.e., over the fracture pressure), the wall of the well can be destroyed and mud penetrates into the reservoir, the drill string can be stuck, and the drilling should be stopped (Skalle et al., 2000). There are different ways to control the pressure in the open hole. One solution is to change the mud density, since this will change the hydrostatic pressure. An evident drawback to this solution is that the change of density includes a long delay. It will also be a problem to achieve precise control.

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Another method to control the pressure is managed pressure drilling (MPD) technology, defined by IADC Underbalanced Operations Committee as "an adaptive drilling process used to precisely control the annular pressure profile throughout the well bore". The objectives are to ascertain the down-hole pressure environment limits and to manage the annular hydraulic pressure profile accordingly (Hannegan et al., 2004). The control solution is the most important part of MPD technology.

State-of-the-art control solutions typically employ conventional PI control applied to the choke. A significant drawback of the control system based on conventional PI control concerns its slow reaction to fast pressure changes, which result from the movements of the drill string. Another drawback is the uncertainty in the modeled bottom-hole pressure, due to uncertainties in the friction and mud compressibility parameters in both the drill string and annulus. Furthermore, the method needs frequent manual tuning, which means that the performance degrades during drilling without continuous re-tuning (Salahshoor et al., 2012).

There is a significant incentive to improve the existing algorithms to efficiently control the critical down-hole pressure. Control systems are conceptually designed to minimize the effects of process variations and environmental influences on the quality of process control. These variations and influences are sometimes significant; thus the conventional PI controllers with constant parameters are unable to control the processes successfully. The main tasks of the controller in such situations are retaining the stability and maintaining the desired performance of the control system. Adaptive control presents an attractive candidate approach to achieving these demanding goals. An adaptive controller adjusts itself to the changes during operation. It recognizes variations in the process and in the environment and adapts the structure and the parameters of the controller accordingly. The adaptation mechanism further automates the control of the process by performing the tasks usually performed by the control engineer, and thus, extends the idea of the feedback loop. Research into control paradigms resulted in the development of two adaptive control techniques, namely model reference adaptive systems (MRAS) and self-tuning regulator (STR).

Adaptive control schemes enable the improved compensation for pressure fluctuations during particularly critical drilling operations with the adaptation of uncertain parameters rather than integral action in the controller. This methodology typically enables faster reaction to changes at set-points and disturbances. Furthermore, adaptive control offers a suitable strategy due to imprecision in the modeling and measurement of well operations. The controller is able to handle large uncertainties as an important factor in the well drilling technology.

The main goal of this paper is to propose a closed-loop adaptive control system for managed pressure drilling (MPD) processes. The proposed adaptive controller aims to achieve the desired MPD process output, i.e. the bottom-hole pressure in the well for real-time operations. The proposed controller is shown to be effective based on the simulation results. A set of adaptive controllers is designed using various methods in the framework of self-tuning controller (STC) and the results are comparatively evaluated with the conventional PI-controller in a simulated well drilling system.

2. Modeling

A dynamic model of the real system is first derived to design the model-based adaptive controllers. Well drilling systems can accurately be modeled by partial differential equations (PDE). To design a MPD control system, a simple nonlinear model is utilized to characterize the main dynamics of the system with sufficient accuracy by using the following equations (Stamnes et al., 2008):

$$\dot{p}_p = a_1 \left(q_{pump} - q_{bit} - \dot{V}_d \right)$$

$$a_1 = \frac{\beta_d}{V_d}$$

$$\dot{p}_c = a_2 \left(q_{bit} + q_{res} + q_{back} - q_{choke} - \dot{V}_a \right)$$

$$a_2 = \frac{\beta_a}{V_a}$$

$$\dot{q}_{bit} = a_3 \left(p_p - p_c \right) - a_4 \left(q_{bit} \right)^2 - a_5 \left(q_{bit} + q_{res} \right)^2 + a_6 h_{bit}$$

$$a_3 = \frac{1}{\left[M_a + M_d \right]}$$

$$a_4 = \frac{F_d}{\left[M_a + M_d \right]}$$

$$a_5 = \frac{F_a}{\left[M_a + M_d \right]}$$

$$a_6 = \frac{\left(\bar{\rho}_d - \bar{\rho}_a \right) g}{\left[M_a + M_d \right]}$$

(1)

As shown, the system includes three states. The bottom-hole pressure can be computed by following equation:

$$p_{bit} = p_p - M_d \dot{q}_{bit} - F_d \left(q_{bit} \right)^2 + \bar{\rho}_d g h_{bit} \tag{2}$$

The model variables and parameters have been summarized in Tables 1 and 2 respectively. Table 3 lists the initial variable values for the derived dynamic model.

Table 1
Model variables

Variable	Description
P_p	Main mud pump pressure
P_c	The pressure just before choke valve
P_{bit}	Bottom hole pressure
q_{bit}	Drill bit flow rate
q_{pump}	Main mud pump flow rate
q_{back}	Back pressure pump flow rate
q_{choke}	Choke valve flow rate
q_{res}	Influx/outflux flow rate of reservoir fluids

3. Methodology

In this paper, a set of diverse self-tuning controllers is developed based upon the general block-diagram architecture displayed in Figure 1. The proposed self-tuning controllers contain an on-line identification stage to estimate the relevant time-dependent model parameters to comply with the different well drilling operation conditions. In the following sections, all the proposed STC's are developed; in all of them the controlled variable is assumed to be P_{bit}, while the manipulated variable is taken to be equal to $u = q_{back} - q_{choke}$.

Table 2
Model parameters

Variable	Description	Value
β_a	Annulus mud bulk modulus (bar)	14000
β_d	Drill string mud bulk modulus (bar)	14000
V_a	Annulus volume (m^3)	96.1327
V_d	Drill string volume (m^3)	28.2743
M_a	Mass coefficient of the annulus ($10^{-5} \times kg/m^4$)	1600
M_d	Mass coefficient of the drill string ($10^{-5} \times kg/m^4$)	5720
F_a	Annulus friction factor	20800
F_d	Drill string friction factor	165000
ρ_a	Annulus density ($10^{-5} \times kg/m^3$)	0.0119
ρ_d	Drill string density ($10^{-5} \times kg/m^3$)	0.0125
h_{bit}	Vertical depth of the drill bit (m)	2000
g	Gravity acceleration (m/s^2)	9.81
q_{res}	Flow rate of reservoir fluids (m^3/s)	0.001
P_0	Pressure outside system (bar)	1

Table 3
Initial Values for Model Variables

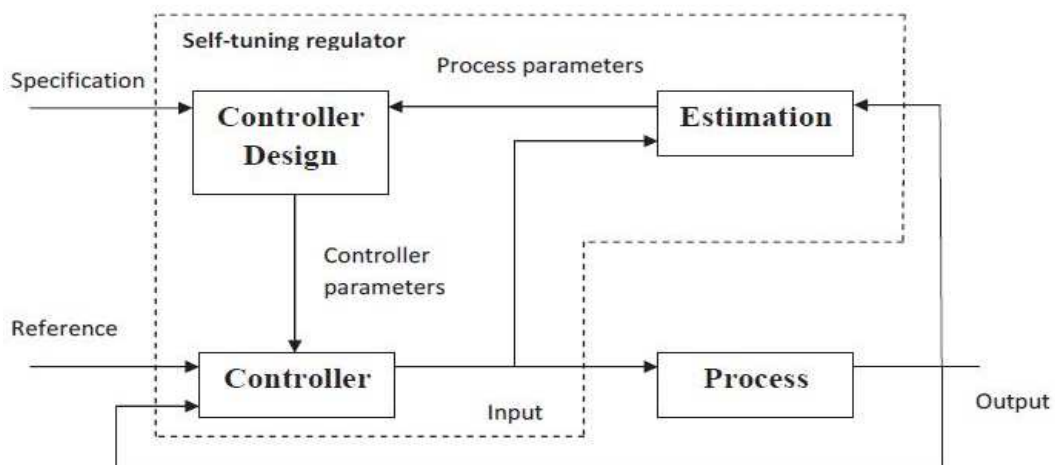| Variable	Description	Value
P_{P0}	Initial main mud pump pressure (bar)	120
P_{c0}	Initial choke valve pressure (bar)	70
q_{bit0}	Initial drill bit flow rate (m^3/s)	0.014

Figure 1
General block diagram of self-tuning controller

The general self-tuning control block diagram, shown in Figure 1, can be thought of as being composed of two loops. The inner loop consists of the process and an ordinary feedback controller with adjustable parameters. The parameters of the controller are then adjusted via the outer loop, which is composed of a recursive parameter estimator and a design calculation block. In this way, the process model and the control design can be updated at each sampling time (Astrom et al., 2008). A set of STC's is developed in the following section the individual blocks of which are developed accordingly.

3.1. On-line identification: recursive least-square (LS) method with adaptive directional forgetting

In the present work, a LS method is recursively developed for the purpose of on-line identification based on an adaptive directional forgetting scheme. The method can be used for the on-line identification of discrete-time processes which are described by the following transfer function:

$$G(z) = \frac{B(z^{-1})}{A(z^{-1})} = \frac{b_1 z^{-1} + b_2 z^{-2} + ... + b_m z^{-m}}{1 + a_1 z^{-1} + a_2 z^{-2} + ... + a_n z^{-n}} z^{-d} \tag{3}$$

The estimated process output in step k ($\hat{y}_k$) is computed on the basis of the process knowledge in the form of the process inputs (u) - outputs (y), using the following recursion formula:

$$\hat{y}_k = \Theta_{k-1}^T \cdot \Phi_k$$

$$\Theta_{k-1}^T = \left[\hat{a}_1,...,\hat{a}_n, \hat{b}_1,...,\hat{b}_m \right]^T \tag{4}$$

$$\Phi_k = \left[-y_{k-1},...,-y_{k-n}, u_{k-d-1},...,u_{k-d-m} \right]^T$$

The vector Θ_{k-1}^T contains the process parameter estimates, computed in the previous time step, and the data vector (Φ_k) contains past output and input values for the computation of the current output $\hat{y}_k$. The up-dated model parameters are then employed for the controller design stage instead of the fixed dynamic model of the process being controlled.

Least square methods are based on the minimization of the sum of prediction errors squares:

$$J_k = \sum_{i=1}^{k} \left(y_i - \Theta_k^T \Phi_i \right)^2 \tag{5}$$

where, y_i denotes the process output at i-th time step and the product of $\Theta_k^T \Phi_i$ represents the predicted process output. Solving this equation at recursive time instants leads to the recursive version of the least square method. The main disadvantage of this ordinary recursive least-square (ORLS) method, however, relates to the absence of time-varying signal weighting. The problem can be tackled by an exponential forgetting factor method which uses forgetting coefficient $\square$ in order to decrease the significance of the past data weights corresponding to the historical time steps. The exponential forgetting method can further be improved by an adaptive directional forgetting which changes forgetting coefficient with respect to the significance of the input and output signal. Process parameters can then be updated using the following recursive equations (LJUNG, 1999):

$$\Theta_k = \Theta_{k-1} + \frac{C_{k-1} \cdot \Phi_k}{1+\xi} \cdot \left(y_k - \Theta_{k-1}^T \Phi_k \right)$$

$$\xi = \Phi_k^T \cdot C_{k-1} \cdot \Phi_k$$

$$C_k = C_{k-1} - \frac{C_{k-1} \cdot \Phi_k \cdot \Phi_k^T \cdot C_{k-1}}{\varepsilon^{-1} + \xi}$$

$$\varepsilon = \varphi_{k-1} - \frac{1-\varphi_{k-1}}{\xi}$$

$$\varphi_k = \frac{1}{1+(1+\rho)\left\{ \ln(1+\xi) + \left[\frac{(v_k+1)\eta}{1+\xi+\eta} - 1 \right] \frac{\xi}{1+\xi} \right\}} \tag{6}$$

$$v_k = \varphi_{k-1}\left(v_{k-1} + 1 \right)$$

$$\eta = \frac{\left(y_k - \Theta_{k-1}^T \Phi_k \right)^2}{\lambda_k}$$

$$\lambda_k = \varphi_{k-1}\left[\lambda_{k-1} + \frac{\left(y_k - \Theta_{k-1}^T \Phi_k \right)^2}{1+\xi} \right]$$

3.2. Controller design

In this section, five control laws are developed to realize the proposed self-tuning controllers using the relevant literature (Clarke et al., 1980).

a. Adaptive Ziegler-Nichols PI-controller based on trapezoidal method of discretization

Control law for this method can be described as follows:

$$u_k = K_p \left[e_k - e_{k-1} + \frac{T_0}{T_I} \frac{e_k - e_{k-1}}{2} \right] + u_{k-1} \tag{7}$$

$$e_k = w_k - y_k$$

where, w_k, y_k, and u_k denote current reference signal, current process output, and current process input respectively (Ziegler et al., 1942). This form of control law can be written in the following feedback form:

$$u_k = q_0 e_k + q_1 e_{k-1} + u_{k-1} \tag{8}$$

where,

$$q_0 = K_p \left(1 + \frac{T_0}{2T_I} \right)$$

$$q_1 = -K_p \left(1 - \frac{T_0}{2T_I} \right) \tag{9}$$

$$K_p = 0.6K_{pu}$$

$$T_I = 0.5T_u$$

Variables K_{pu} and T_u indicate ultimate gain and ultimate period respectively, which must be recursively calculated at each time step. The basic idea of this calculation is to find the required

feedback gain to establish the stability border of the closed-loop. For process transfer function defined by Equation 3, the characteristic equation due to the final closed-loop is:

$$A(z) + K_p \cdot B(z) = 0 \tag{10}$$

where, K_p is feedback gain. When the closed-loop system is on the stability border, one or more roots of its characteristic equation can be on the stability border and the other roots are stable. In terms of the complex variable z, the stable region includes the inner of the unit circle, and hence the stability border is denoted by the unit circle circumference, while the rest denotes the unstable region. The ultimate root $z=1$ must be omitted in calculation, because it locates on the asymptotic stability border and thus its ultimate period cannot be calculated. There are two possible types of root positions when calculating ultimate gain and ultimate period (Astrom et al., 2008):

- Two complex conjugated roots are on unit circle and the other roots are not unstable;
- Root $z = -1$ and the other roots are not unstable.

b. Adaptive LQ controller

The general control law for an adaptive LQ controller is given by:

$$u_k = \frac{1}{p_0}\left(r_0 w_k + r_1 w_{k-1} - q_0 y_k - q_1 y_{k-1} - p_1 u_{k-1}\right) \tag{11}$$

where, parameters r_0, r_1, q_0, q_1, and p_1 are calculated by solving the following Diophantine equations:

$$A\left(z^{-1}\right)P\left(z^{-1}\right) + B\left(z^{-1}\right)Q\left(z^{-1}\right) = D\left(z^{-1}\right)$$
$$B\left(z^{-1}\right)R\left(z^{-1}\right) + F\left(z^{-1}\right)S\left(z^{-1}\right) = D\left(z^{-1}\right) \tag{12}$$

where, polynomials can be represented as:

$$A\left(z^{-1}\right) = 1 + \hat{a}_1 z^{-1} + \hat{a}_2 z^{-2} \qquad Q\left(z^{-1}\right) = q_0 + q_1 z^{-1}$$
$$B\left(z^{-1}\right) = \hat{b}_1 z^{-1} + \hat{b}_2 z^{-2} \qquad R\left(z^{-1}\right) = r_0 + r_1 z^{-1} \tag{13}$$
$$P\left(z^{-1}\right) = p_0 + p_1 z^{-1} \qquad D\left(z^{-1}\right) = 1 + d_1 z^{-1} + d_2 z^{-2}$$

$S(z^{-1})$ denotes any appropriate polynomial (Zoran, 2000). The coefficients of the relevant polynomials are calculated using the following relationships:

$$d_1 = \frac{m_1}{\delta + m_2} \qquad \lambda = \frac{m_0}{2} - m_2 + \sqrt{\left(\frac{m_0}{2} + m_2\right)^2 - m_1^2}$$
$$d_2 = \frac{m_2}{\delta} \qquad m_0 = \varphi\left(1 + a_1^2 + a_2^2\right) + b_1^2 + b_2^2 \tag{14}$$
$$\delta = \frac{\lambda + \sqrt{\lambda^2 - 4m_2^2}}{2a} \qquad m_1 = \varphi\left(a_1 + a_1 a_2\right) + b_1 b_2$$
$$m_2 = \varphi a_2$$

$F(z^{-1})$ depends on the desired reference signal type that could be expressed in the general forms of *steps*, *ramps* or *sin waves*.

If *ramp* is used as the reference signal type, $F(z^{-1})$ can be given by:

$$F\left(z^{-1}\right) = 1 - 2z^{-1} + z^{-2} \tag{15}$$

c. Adaptive deadbeat controller

The control law for an adaptive deadbeat controller can be specified as:

$$u_k = r_0 w_k - q_0 y_k - q_1 y_{k-1} - p_1 u_{k-1} \tag{16}$$

where, controller parameters r_0, q_0, q_1, and p_1 are calculated by solving the following Diophantine equations:

$$A\left(z^{-1}\right)P\left(z^{-1}\right)+B\left(z^{-1}\right)Q\left(z^{-1}\right)=1$$
$$1-B\left(z^{-1}\right)R\left(z^{-1}\right)=\left(1-z^{-1}\right)S\left(z^{-1}\right) \tag{17}$$

The polynomials are defined as by:

$$A\left(z^{-1}\right)=1+\hat{a}_1 z^{-1}+\hat{a}_2 z^{-2} \qquad\qquad Q\left(z^{-1}\right)=q_0+q_1 z^{-1}$$
$$B\left(z^{-1}\right)=\hat{b}_1 z^{-1}+\hat{b}_2 z^{-2} \qquad\qquad R\left(z^{-1}\right)=r_0 \tag{18}$$
$$P\left(z^{-1}\right)=1+p_1 z^{-1} \qquad\qquad S\left(z^{-1}\right)=s_0+s_1 z^{-1}$$

By solving the Diophantine equations, controller parameters could be found (Bobál et al., 1999).

d. Adaptive Astrom's controller

The control law for the adaptive Astrom's controller reads:

$$u_k = u_{PI,k}+u_{D,k}$$

$$u_{PI,k}=K_p\left[y_{k-1}-y_k+\frac{T_0}{2T_I}\left(w_k-y_k+w_{k-1}-y_{k-1}\right)+\beta\left(w_k-w_{k-1}\right)\right]+u_{PI,k-1} \tag{19}$$

$$u_{D,k}=\frac{T_D}{T_D+T_0\alpha}\left[K_p\alpha\left(y_{k-4}-y_k\right)+u_{D,k-1}\right]$$

where, α denotes filtration coefficient used to filter the process output signal. The filter time constant is $T_d=\dfrac{T_D}{\alpha}$, in which α is usually set in the open interval of (3,20), i.e. $3<\alpha<20$; β denotes the weight of reference signal in the proportional component of controller and should be selected as $0<\beta\leq 1$. T_0 indicates the process sample time. The constants are set on the basis of the following equations:

$$K_p=0.6K_{pu}$$
$$T_I=0.5T_u \tag{20}$$
$$T_D=0.125T_u$$

where, K_{pu} and T_u are ultimate gain and period respectively (Åström et al., 1977).

e. Adaptive generic pole placement controller

The control law for this approach can be defined by the following equation:

$$u_k=\frac{1}{p_0}\left(r_0 w_k+r_1 w_{k-1}-q_0 y_k-q_1 y_{k-1}-p_1 u_{k-1}\right) \tag{21}$$

The relevant control parameters are calculated by solving the following Diophantine equations:

$$A\left(z^{-1}\right)P\left(z^{-1}\right)+B\left(z^{-1}\right)Q\left(z^{-1}\right)=D\left(z^{-1}\right)$$
$$B\left(z^{-1}\right)R\left(z^{-1}\right)+F\left(z^{-1}\right)S\left(z^{-1}\right)=D\left(z^{-1}\right) \tag{22}$$

The method looks like the LQ controller except for the polynomial D that is a characteristic polynomial. The coefficients of this polynomial are represented in the form of a vector which shows the positions of the desired closed-loop poles (Ali, 2004).

4. Simulation and results

4.1. Main drilling procedure, pipe connection

Herein, the responses of the various process variables during the main drilling procedure at the time of pipe connection and/or drilling trips are presented. The following scenarios are organized to take

place in the simulation (Salahshoor et al., 2012):

- Ramp down main mud pump: at time = 50 seconds, the set point for the main mud pump flow rate is set to zero.
- Trip out drill string: at time = 50 seconds, the set point for the drill bit position is increased by 27 meters, representing one stand of pipe.
- Trip in drill string: at time = 100 seconds, the drill bit position set point is set back to its original value of -2000 meters.
- Ramp up main mud pump: at time = 100 seconds, the mud pump flow rate set point is set back to 0.0167 m^3/s.

An additional white noise with a variance of 50 is added to the system to mimic outer unknown disturbances. Furthermore, it is assumed that there is a kick in the well as usually occurs in practice. The parameter values and initial values of the model variables used in the conducted simulations are tabulated in Tables 2 and 3 respectively.

The proposed controllers together with the conventional PI controller are simulated in Matlab using the same model parameters listed in Table 2. The following two criteria are used to make the comparisons between the performances of a conventional PI-controller and the developed self-tuning controllers:

- Mean Square Error
- Mean Absolute Error

Table 4
Comparison between different STC methods for the main drilling procedure during pipe connection

Item	Method	MSE	MAE
1	Adaptive Ziegler-Nichols PI-controller based on trapezoidal method of discretization	0.0159	0.0023
2	Adaptive LQ controller	0.1539	0.0078
3	Adaptive deadbeat controller	0.1495	0.0071
4	Adaptive Astrom's controller	0.1087	0.0081
5	Adaptive generic pole placement controller	0.1495	0.0071
6	Conventional PI-controller	20.823	10.428

Table 4 clearly indicates that the family of the developed self-tuning controllers presents better performances than the conventional PI-controller to regulate the induced disturbances in pressure, which are caused by changing the main mud pump flow rate and the tripping out and tripping in, as well as the added white noise to mimic the outer unknown disturbances.

The simulation tests have shown that the developed self-tuning controllers approximately present the same results, which are completely distinct and better than the alternative PI-controller results. Thus, for the convenience, only the results of adaptive LQ controller are comparatively illustrated with the conventional PI-controller results in Figure 2.

4.2. Reference tracking performance

A test procedure is conducted in which the reference signal, i.e. bottom-hole pressure, changes periodically as follows:

Set point is first set to 400 bar. The set point is then decreased to 200 bar after 100 seconds and, following that, it is again raised to the initial value after 100 seconds. Next, the conducted experiment

is repeated again. While the simulation is running, the height of well and mud pump flow rate are kept constant.
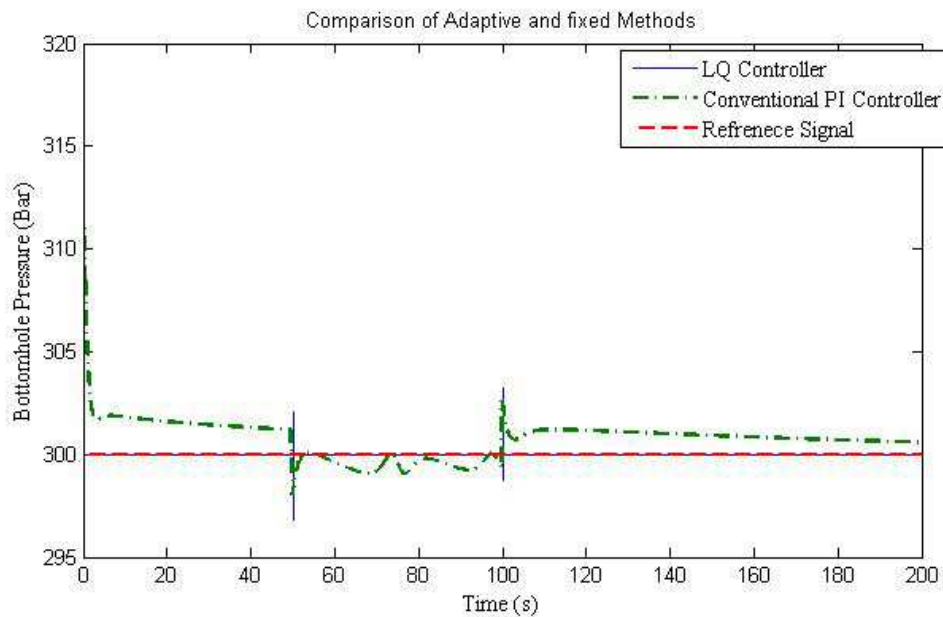

Figure 2

Comparison between the performances of adaptive LQ controller and PI-controller in the main drilling procedure during pipe connection

Mean square and mean absolute error are considered as the measuring criteria to enable comparisons of all the developed STC methods with the alternative PI-controller. The calculated measures are summarized in Table 5. The results of the conventional PI-controller and the adaptive LQ-controller are displayed in Figure 3. The same test scenario was conducted to evaluate the performance of Astrom controller versus the other developed self-tuning controllers. Figure 4 confirms that the Astrom controller behaves worse than the other developed STC controllers. The observed performances indicate that the other self-tuning controllers almost have the same results. However, again because of simplicity, only the outcome of adaptive LQ-controller is comparatively illustrated in comparison with the conventional PI-controller.

Table 5

Comparison between different developed STC methods for reference tracking control objective

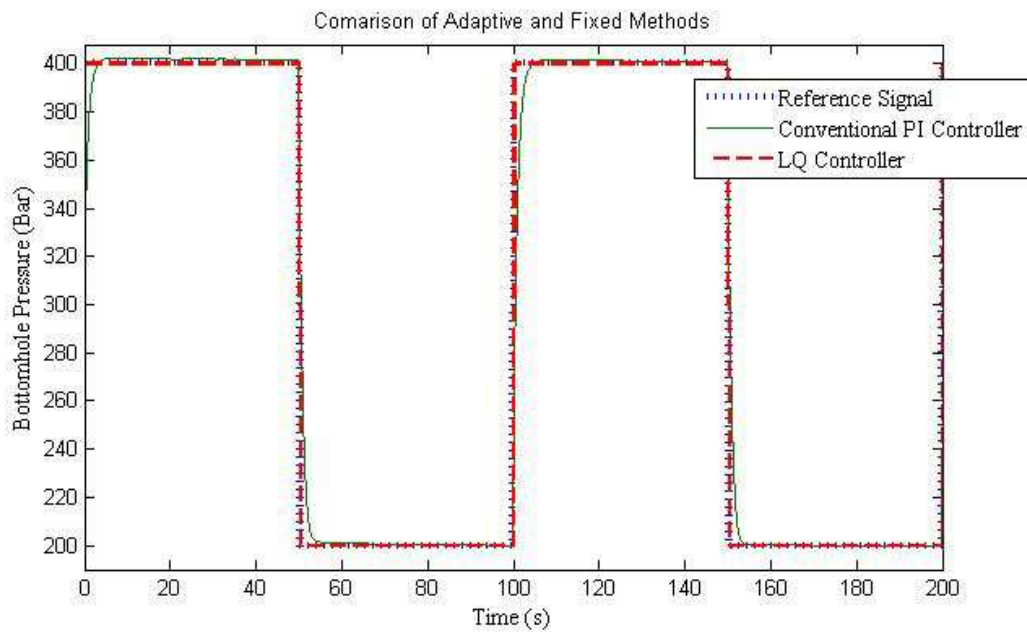| Item	Method	MSE	MAE
1	Adaptive Ziegler-Nichols PI-controller based on trapezoidal method of discretization	52.8092	0.3843
2	Adaptive LQ controller	52.7219	0.3928
3	Adaptive deadbeat controller	52.7951	0.3886
4	Adaptive Astrom's controller	931.5052	7.9839
5	Adaptive generic pole placement controller	52.7950	0.3884
6	Conventional PI-controller	333.8837	4.0291

Figure 3
The responses for reference tracking control objective of Adaptive LQ controller and PI-controller
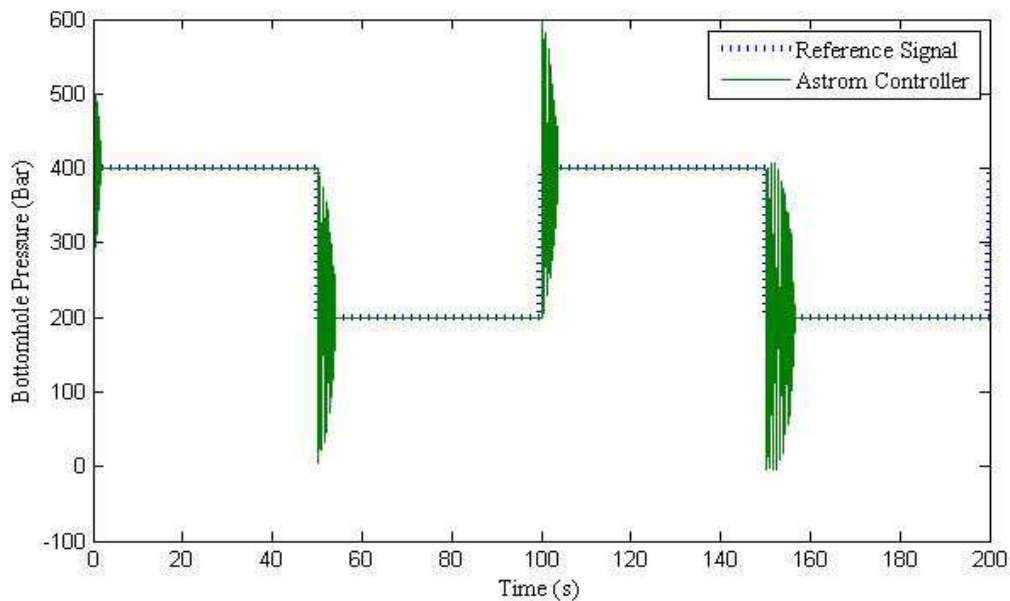

Figure 4
Astrom controller response for reference tracking control objective

5. Conclusions

In the current paper, a family of diverse self-tuning controllers has been developed to tackle the challenging control issues of well drilling operations on the basis of the MWD methodology. The paper clearly illustrated that the precise control could be achieved by using the developed self-tuning control methods. Diverse sets of test scenarios were organized to comparatively evaluate the performances of the developed STC controllers in dealing with some typical regulatory and reference tracking control objectives. The obtained performance outcomes clearly outperformed the alternative

performance of the conventional PI-controller. Moreover, the classical PI-control method could not manage to operate well all the times due to the regular manual re-tuning requisite to cope with time-varying circumstances occurring during the well drilling operations. The developed self-tuning control methods were shown to be capable of efficiently dealing with this problem and the induced uncertainties, which emulated all the possible time-varying sources affecting the actual well drilling operations. The combined use of OLGA and Matlab simulation environments can offer better realization media to present the actual practical situations encountered in well drilling operations; this will be pursued as future research works.

Nomenclature

MPD	: Managed pressure drilling
MSE	: Mean square error
MAE	: Mean absolute error
MRAS	: Model reference adaptive systems
ORLS	: Ordinary recursive least-square
PDE	: Partial differential equations
PI	: Proportional-integral
STC	: Self-tuning control
STR	: Self-tuning regulator

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