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Improved Bottomhole Pressure Control with Wired Drillpipe and Physics-Based Models

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Abstract

Wired Drillpipe (WDP) technology provides two-way and high speed measurements from bottom hole and along-string sensors. The data offered by WDP technology has maximum benefit when applied in an automation system or as a real-time advisory tool. Improved control is demonstrated for Managed Pressure Drilling (MPD) with the use of high-speed telemetry and physics-based models. Stabilizing and minimizing pressure within an acceptable bound leads to higher and more consistent Rate of Penetration (ROP).

MPD control is challenging due to tight pressure windows and the nonlinearity of the choke and pump response on Bottom Hole Pressure (BHP). This work demonstrates a new Hammerstein-Wiener nonlinear model predictive controller for BHP regulation in drilling. Hammerstein-Wiener models employ input and output static nonlinear blocks before and after linear dynamics blocks and thereby simplify the controller design. The control performance is evaluated in scenarios such as drilling, pipe connections, and kick attenuation. A physics-based drilling simulator, WeMod, is used for model identification and control performance evaluation.

The control performance of the new nonlinear controller is compared to conventional controllers in various scenarios. Because of the interconnected multivariable and nonlinear nature of the drilling operation, conventional controllers show severe limitations. In a first scenario, the performance of set point tracking during normal drilling operation is compared. By changing the set point of the BHP, the conventional controller manipulates only the choke valve opening while the nonlinear controller moves choke valve opening, mud pump, and back pressure pump simultaneously. In a second scenario, a pipe connection of a typical drillpipe stand is demonstrated. The conventional controller is not able to regulate the BHP by adjusting the choke valve only. Although a linear version of the controller is able to exploit multivariable relationships, absence of the nonlinear relationships results in severe oscillation when the operational range is shifted outside of the training region. The nonlinear controller maintains a BHP within ±1 bar of the requested set point. A third scenario investigates the kick attenuation performance of conventional and nonlinear control algorithms. The nonlinear controller attenuates the kick within well control conditions, without requiring a well shut-in procedure.

Recent advances in drilling simulators and the reliability of the WDP data highway have enabled tighter BHP control. This study presents a robust method to control BHP by applying Hammerstein-Wiener models in an efficient model predictive controller. The proposed methods have been validated in the downstream industry, but are applied for the first time to drilling with nonlinear control functionality. The multivariable control adjusts three main manipulated variables in MPD simultaneously.

Introduction

The recent downturn of the crude oil market motivates improvements in cost effective oil and gas well manufacturing and production. Automation is one possible solution to minimize costs and well completion time. Automation systems can improve safety and convenience and enable optimization strategies. The oil well drilling industry is transitioning to automation systems as downhole sensors, communication, and control technology improves. Thanks to modern telemetry and integration of control systems in new drilling rig designs, several opportunities are opened for Managed Pressure Drilling (MPD) automation and optimization strategies. One of these technologies is Model Predictive Control (MPC). MPC has successfully been applied in many industries (Qin and Badgwell 2003). MPC vendors report that over 4,600 MPC applications were in use by the early 2000s with most applications in the downstream industry. Several features make the technology attractive to the drilling industry. First, MPC has a prediction feature that employs a process model, either determined from data or from physics-based simulators. This feature predicts future constraint violations and anticipates behavior of the process in advance. Processes that have long time constants and time delay or inverse response can be effectively managed. Second, MPC deals with multiple variables at a time, considering the coupling effect between variables. It is able to control multi-input and multi-output (MIMO) systems with single-input and single-output control (SISO) systems are typically implemented with less advanced methods such as Proportional, Integral, and Derivative (PID) control. Third, MPC accommodates nonlinear processes by using Nonlinear Programming Solvers (NLP) and efficient methods to discretize the control and prediction horizon. Fourth, MPC has a range feature that specifies an acceptable control range instead of always driving to a desired target set point. This gives more freedom to operate within an upper and lower range or to drive to a limit, especially when the system has more than one controlled variable (*CV*). The range control feature can reduce conflicted situations when set points for individual *CV*s are simultaneously unachievable. Fifth, MPC allows optimization strategies to push the operation to a more beneficial point, while keeping within an acceptable range. All of these advantages are compared to the well-known PID controller that has the advantage of simple implementation and tuning.

There are the several characteristics of MPD that are improved with MPC technology. First, it is critical to regulate the BHP within a pressure window during MPD operations. Low pressures lead to unexpected gas influx (kick) and high pressures lead to formation damage or lost drilling fluid (mud) circulation. Lower pressure has the effect of increasing ROP because it reduces the chip hold-down effect (McLennan 1997). Related studies demonstrate this benefit by using simplified pressure hydraulics and an ROP model (Asgharzadeh Shishavan 2015, Asgharzadeh Shishavan 2014). The set range control and optimization functionality of MPC are important for these multivariate operation criteria. Second, in comparison to conventional drilling operation, MPD has more manipulated variables (*MV*s) such as choke valve, main mud pump and backpressure pump that move in coordination to maintain a BHP. All three *MV*s are adjusted simultaneously by exploiting the multivariate capabilities of MPC. Lastly, the inherent nonlinear and saccadic nature of drilling is a challenge for the application of automation. **Fig. 1** shows the nonlinearity of the drilling operation between the main variables. The simulated data is obtained from a detailed physics-based drilling simulator, WeMod. A full nonlinear model can be applied to control MPD automation but there are different types of nonlinear models that have been demonstrated. Many previous research studies in drilling automation have established reduced order models by capturing the main dynamics of the drilling process (Nygaard 2005, Nygaard 2006, Kaasa 2007, Siahaan 2008). Although

using simplified low order models reduces the computational time significantly, solving the numerical optimization problem in the MPC algorithm with nonlinear equations is still computationally demanding for real-time control purposes. Moreover, those models use several variables that are not measured and must be estimated. This estimation step adds an additional layer of complexity and computational burden. In contrast with a first principles model, an empirical step response model such as those used in linear Model Predictive Control (LMPC) are widely used in many industries. However, these linear models are not sufficient to capture the nonlinear nature of drilling. Hammerstein-Wiener models are the most widely implemented method of empirical nonlinear models in industry (Ławryńczuk 2013, 2014). The Hammerstein-Wiener models employ input and output static nonlinear blocks before and after the linear dynamic blocks. Because the nonlinear portions of the model are not included in the MPC calculation, the computational burden is significantly reduced. This study demonstrates a Hammerstein-Wiener based NMPC for BHP regulation in drilling. The control performance of the Hammerstein-Wiener based NMPC is compared to the ubiquitous PID controller in various scenarios that frequently occur in drilling operations, such as a pipe connection procedure and with unexpected gas influx.

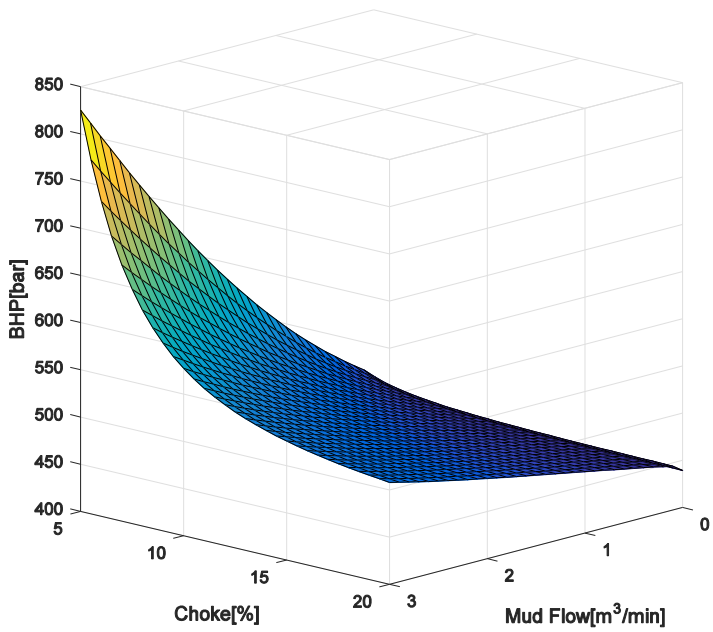


Fig. 1 — Nonlinearity analysis of drilling operation

Hammerstein-Wiener based Model Predictive Control

The structure of Hammerstein-Wiener NMPC for drilling is detailed in this section. The Hammerstein-Wiener model is an extended form of LMPC. It uses the same algorithm as LMPC to optimize the linear dynamic portion of the model. As such, Hammerstein-Wiener NMPC captures the input and output nonlinearities with the computational robustness and simplicity of LMPC. To add the nonlinear control elements to LMPC, the Hammerstein-Wiener model employs static nonlinearity blocks that process the input and output values of the linear dynamic model block. The static nonlinearity blocks are static functions that are separated from the quadratic programming (QP) optimization problems in the MPC algorithm (K.P. Fruzzetti 1997, Sandra J. 1997). Therefore, it allows a gain-scheduling concept for a nonlinear process without significantly increasing the computational complexity. As shown in **Fig. 2**, the linear dynamic model (**G**) is located in between the input and output static nonlinearity blocks (**F** and **H**).

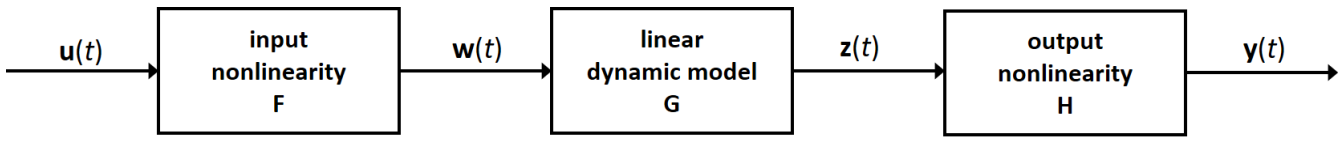


Fig. 2 — Structure of the Hammerstein-Wiener Model

Various types of models can be used for the linear dynamic model. In this study, a state space model is chosen over other types such as a Finite Impulse Response (FIR) model. **Eq. (1) and (4)** represent the input and output nonlinearity blocks (**F**, **H**) respectively and both (2) and (3) describe the state space form of the linear dynamic model (**G**):

$$\mathbf{w}(t) = \mathbf{F}\big(\mathbf{u}(t)\big) \tag{1}$$

$$\frac{d\mathbf{x}(t)}{dt} = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{w}(t) \tag{2}$$

$$\mathbf{z}(t) = \mathbf{C}\mathbf{x}(t) \tag{3}$$

$$\mathbf{y}(t) = \mathbf{H}(\mathbf{z}(t)) \tag{4}$$

where, the vector $\mathbf{u}(t) \in \mathbf{R}^{\boldsymbol{m}}$ and $\mathbf{w}(t) \in \mathbf{R}^{\boldsymbol{m}}$ are the input variables of the input nonlinearity block and linear dynamic model block, respectively. The input value, $\mathbf{u}(t)$, is the actual input value from the process and is converted to an internal variable $\mathbf{w}(t)$ by the input nonlinearity function **F**. The vector $\mathbf{x}(t) \in \mathbf{R}^{\boldsymbol{n}}$ represents the state variable of the state space model. The vectors $\mathbf{z}(t) \in \mathbf{R}^{\boldsymbol{l}}$ and $\mathbf{y}(t) \in \mathbf{R}^{\boldsymbol{l}}$ are the output variables of the linear dynamic model and output nonlinearity block, respectively. Similar to **u** and **w**, internal variable $\mathbf{z}(t)$ is converted to an actual prediction variable $\mathbf{y}(t)$ through the output nonlinearity block **H**. **A**, **B** and **C** denote the state, input, and output matrix of the state space model. The function **F** and **H** in the nonlinearity blocks could be a nonlinear relationship such as a polynomial, power series, or piecewise linear function. In this study, we use the piecewise linear function for nonlinearity blocks discussed in the case study section.

The Hammerstein-Wiener model is utilized in the MPC platform in two main steps: 'Prediction' and 'Optimization'. In the prediction step, a sequence of future moves of the *CV*s is predicted by processing the set of past movements of the *MV*s through the process dynamics model. Then, in the optimization step, a sequence of optimized future *MV*s movements is calculated by solving a QP optimization problem. The QP objective function is designed to minimize the difference between the predicted value and desired trajectory of the *CV*s. The first *MV* move of the sequence is implemented to modify the choke position and pump rates. The entire procedure is repeated for every sampling time. The additional steps for the Hammerstein-Wiener model are the processing of input and output values for the LMPC. This involves reverse processing the actual *CV* targets or ranges through the inverse nonlinearity block before it goes into the MPC block. Additionally, the internal *MV* output which is reverse transformed and applied to the process. Note that the nonlinearity blocks are inverted for the control schematic. The structure of the Hammerstein-Wiener based MPC system is shown in **Fig. 3**.

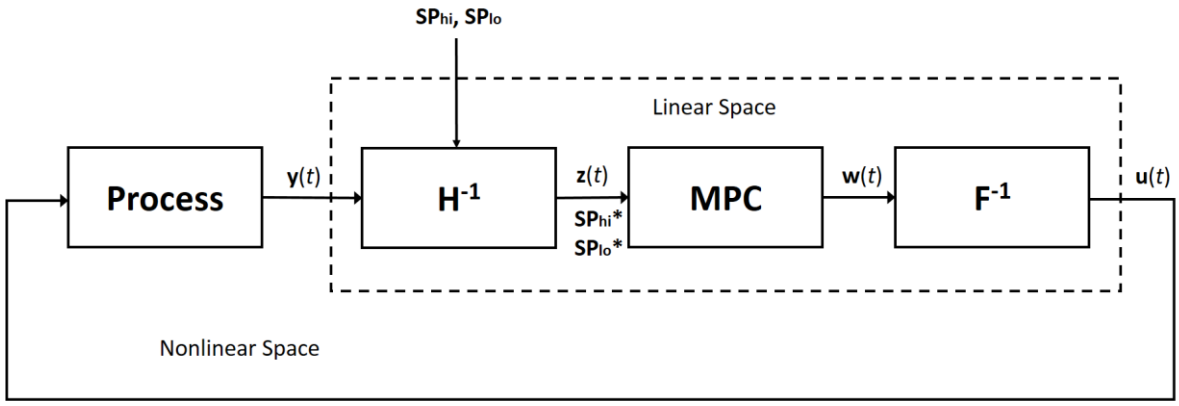


Fig. 3 — Structure of the Hammerstein-Wiener based MPC system

Mathematical expressions of the Hammerstein-Wiener MPC are shown below. The upper and lower bound of control input (sp_{hi}, sp_{lo}) and control input (y) are transformed by inverse output nonlinearity function H^{-1} shown in **Eq. 5** and **6**. The control output (w) is transformed by inverse input nonlinearity function F^{-1} shown in **Eq. 7**.

$$sp_{hi}^*(t) = H^{-1}\left(sp_{hi}(t)\right) \quad and \quad sp_{lo}^*(t) = H^{-1}\left(sp_{lo}(t)\right) \tag{5}$$

$$z(t) = H^{-1}\big(y(t)\big) \tag{6}$$

$$u(t) = F^{-1}\big(w(t)\big) \tag{7}$$

The QP objective function used in this study is the l_1 norm type objective which has many advantages especially for the multiple objective optimization (Hedengren 2014). The l_1 norm objective function with the parameters associated with Hammerstein-Wiener structure is shown in **Eq. 8 and Table 1**.

$$\begin{gathered}
\min_{z,w} \phi = Q_{hi}^T(e_{hi}) + Q_{lo}^T(e_{lo}) + (z)^T c_z + (w)^T c_w + (\Delta w)^T c_{\Delta w} \\
s.t. \;\; 0 = f\left(\frac{dx}{dt}, x, z, w\right) \\
0 = g(x, z, w) \\
0 \le h(x, z, w) \\
\tau_c \frac{dz_{t,hi}}{dt} + z_{t,hi} = sp_{hi}^* \\
\tau_c \frac{dz_{t,lo}}{dt} + z_{t,lo} = sp_{lo}^* \\
e_{hi} \ge \left(z - z_{t,hi}\right) \\
e_{lo} \ge \left(z_{t,lo} - z\right) \\
e_{hi}, e_{lo} \ge 0
\end{gathered} \tag{8}$$

Table 1. Summary of parameters used in the l_1-norm objective function and LMPC QP solution

Parameter	Description
sp_{hi}, sp_{lo}, sp_{hi}^*, sp_{lo}^*	actual and transformed (*) value of upper and lower bound
ϕ	objective function
z_m	model output values $\left(z_{m,0}, \ldots, z_{m,n}\right)^T$ or predicted output values
w, Δw	inputs, input change
x	states

$z_{t,hi}$, $z_{t,lo}$	desired trajectory dead-band
Q_{hi}, Q_{lo}	penalty outside trajectory dead-band or weighting factor
c_z, c_w, $c_{\Delta w}$	cost of z, w and Δw, respectively
f	equation residuals
g	output function
h	inequality constraints
τ_c	time constant of desired controlled variable response
e_{lo}	slack variable below the trajectory dead-band
e_{hi}	slack variable above the trajectory dead-band

Case Study

In this section, the wellbore condition and scenarios are described. A vertical geometry well is simulated with topside MPD rig equipment. The MPD rig has a choke valve, a main mud pump, and a back pressure pump as adjustable parameters for BHP regulation. The detailed parameters of the wellbore condition are referred from the other study (Gravdal 2010) and shown in **Table 2**. For the BHP measurement, WDP is used for all scenarios. Unlike the traditional mud-pulse telemetry, WDP increases the data transmission rate up to 10^4-10^5 bits per second and provides reliable bottomhole data to the surface to enable MPD control systems in real-time (Pixton 2014).

Table 2. Wellbore conditions

Parameter	Value (AES)	Value (SI)
Well depth	11,800 ft	3,600 m
Riser inner diameter	19''	0.48 m
Water depth	590 ft	180 m
Casing inner diameter	9''	0.23 m
Casing depth	7,100 ft	2,164 m
Drill string average outer diameter	4.5''	0.12 m
BHA length	150 ft	45.7 m
BHA average outer diameter	6.7''	0.17 m
Open hole/bit size	8.5''	0.2 m
Reservoir depth	9840 ft	3,000 m
Reservoir Pore Pressure	401.0 bar/1.364 s.g.	401.0e+05 Pa/1.364 s.g.
Initial mud density	1.24 s.g.	1.24 s.g.

An important factor in the MPC design is the relationship between inputs and outputs. **Table 3** shows the MPC design matrix with +/- signs that denote the positive or negative gain relationships. Various process dynamics models could be used for these relationships such as transfer function or state space forms that have equivalency relationships. These types of models represent both transient behavior and steady state gain. In Table 1, BHP (p_{bit}) is the main controlled variable (CV) for the normal operation and pipe connection procedure. The mud flow balance (q_{bal}) is considered as an additional CV for kick attenuation. The three MPD manipulated variables (MVs) are choke opening (z_{choke}), back pressure pump (q_{back}), and main mud pump (q_p). All three variables play a role as MVs except during the pipe connection procedure where the main mud flow is manually ramped up and down. Therefore, the main mud flow is considered as a ramped input for the pipe connection procedure. The MPC algorithm reflects the influence

of the ramping sequence on the control calculation so that it compensates for the loss or gain of mud flow before it drives the BHP away from a target value.

Table 3. Model matrix with the positive and negative interaction between CVs and MV/DVs

		MV / DV		
		z_{choke}	q_{back}	q_p
CV	P_{bit}	-	+	+
	q_{bal}	-	+	+

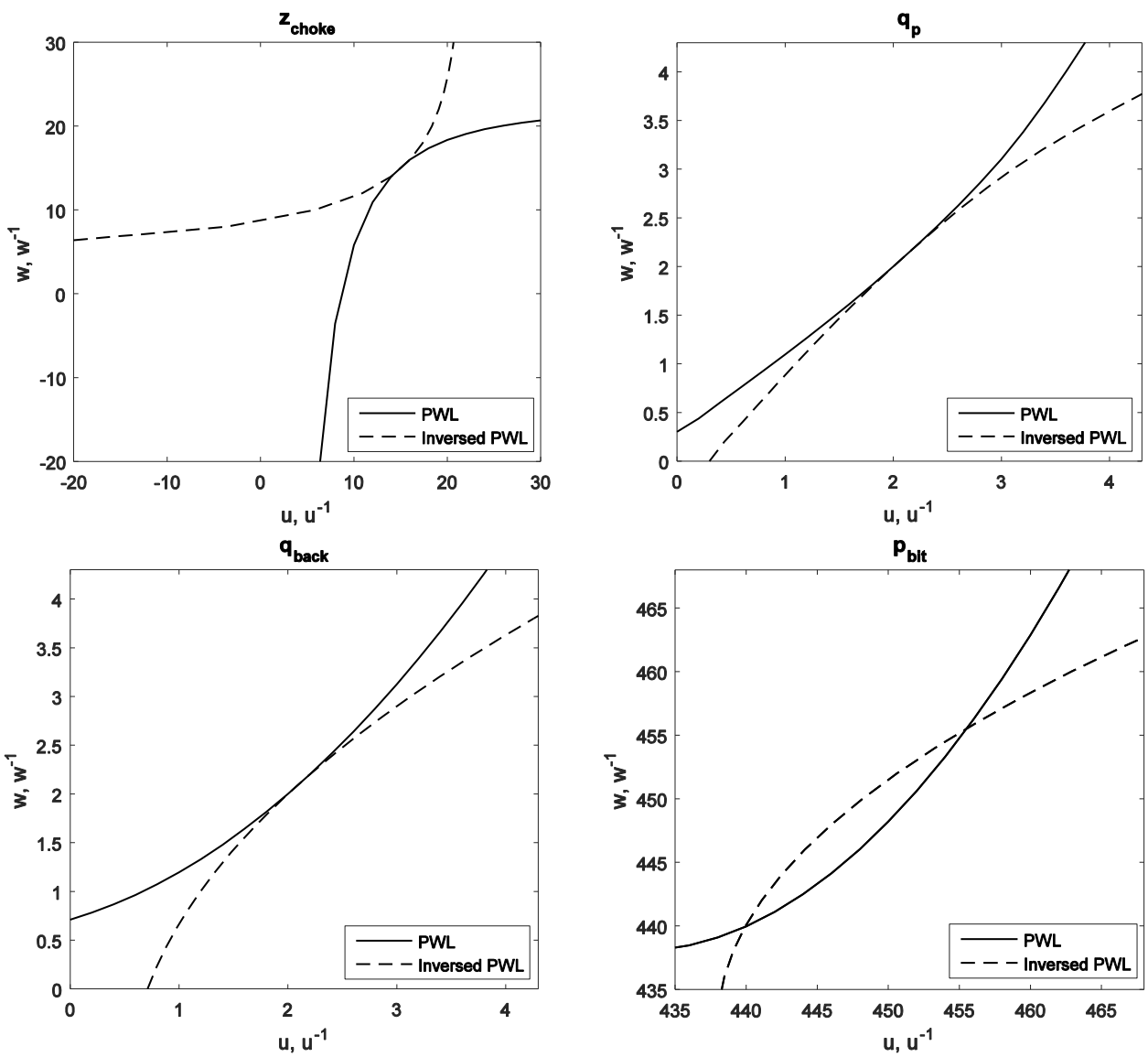


Fig. 4 — Piecewise linear function for nonlinearity blocks

Normal drilling

Maintaining the wellbore pressure within a pressure window is one of the highest priorities for normal drilling. Within this pressure window, it is best to maintain pressure near the lower limit of pore pressure for maximum ROP. This is not only to reduce mud loss in certain zones, but also because the pressure difference between wellbore and reservoir generate the chip hold-down effect that causes lower ROP (McLennan 1997). Although lower pressure is desired, approaching the reservoir pore pressure increases the possibility of a gas influx. In the normal drilling scenario, two aspects of NMPC are tested. The first is control performance when the set point or set range is changed, called servo control. The set range of the BHP is changed to sufficiently cover a wide operation range. All three MVs (choke opening, main mud pump flow, and back pressure pump) are actively adjusted to meet the new set range of BHP. The weighting factors in the objective function for each MV are tuned to adjust the relative movements among the MVs. The second aspect is related to an optimization feature of MPC. While the BHP is maintained in the desired set range, the linear programing (LP) objectives for the CVs and MVs drive the variables to the upper or lower limit of each. The parameters c_z and c_w in Eq. 8 are the cost parameters for the minimized LP objectives. They are positive constants to push the BHP to the low value of the range near the pore pressure.

Pipe connection

Pipe connection is the addition of multiple sections of drilling pipe to the existing drill string as the drill bit penetrates the formation. Based on a rough calculation with typical ROP and length of a single pipe stand, the pipe connection procedure takes place every one to three hours (Stamnes 2008). During the procedure, the main mud pump flowrate is ramped down to zero and waits until a new pipe is added and then ramped back up to normal drilling operation. The BHP is formed by three different sources, hydrostatic pressure of mud and cuttings, annulus friction pressure loss by mud flow rate, and back-pressure exerted by the back-pressure pump and choke valve. By ramping down the main mud flow rate, one of the pressure sources exerted on the bottomhole is lost. The back-pressure system includes the choke valve and back-pressure pump and is adjusted to compensate for the BHP decrement. Note that the hydrostatic pressure does not change during the entire pipe connection procedure. In the MPC configuration for pipe connection procedure, the main mud pump flowrate (q_p) switches from an optimized degree of freedom to a fixed ramp input. The predefined ramping sequence of the mud flowrate (q_p) is not a part of the MPC output. However, it has a significant effect on the BHP and is therefore considered by MPC calculation. By having this feedforward input in the MPC, the pressure control performance is significantly improved in comparison with the case that fully relies on feedback control.

Kick attenuation

When the drill bit enters a formation that has high reservoir pressure, formation gas may unexpectedly penetrate into the wellbore as the pore pressure exceeds the BHP. The gas influx from the formation may require more aggressive well control methods or may cause loss of well control in extreme circumstances. To prevent such problems, any detected gas influx above a certain threshold required for well control is typically circulated out after the well is shut in. In MPD, the mud pump flowrate and choke valve regulate the BHP without shutting in the well and stopping the drilling process. The kick is conventionally detected by monitoring the mud pit levels or by observing an imbalance between mud pump flow and returning mud. Other kick detection methods include monitoring of unexpected increase in annulus pressure as the dissolved gas escapes the formation or an unexpected decrease in hydrostatic pressure due to the expansion of the dissolved gas as it travels with the mud back to the surface. The control strategy for the BHP should be differentiated between the normal operation and the kick situation. To decrease the high BHP in normal operation, the choke valve opens and the mud pump flowrate decreases. During a kick, the same control actions, however, still allow or even accelerate the gas influx to rise up to the surface through the mud circulation. The strategy in the previous research (Asgharzadeh Shishavan 2015) correctly decreases the choke valve opening and increases the mud pump flowrate by switching the CV from BHP (p_{bit}) to choke

valve pressure (p_c) with a calculated higher set point. The other research proposed a different switching method between BHP control and mass balance control with a PID control algorithm (Zhou 2011). In this study, the mass balance control concept is adopted with an MPC algorithm. The flow balance is added to the BHP control configuration as a second *CV* without additional switching logic. However, by introducing the second *CV*, conflicts potentially arise from physically infeasible constraints of all the *CV*s and *MV*s. These situations are significantly reduced by the aforementioned MPC advantages, such as the range control feature and weight factors for the *CV*s in the objective function to prioritize conflicting objectives. In addition to these, a *CV* prioritization is added to exclude a *CV* from the MPC calculation in a specific condition. The condition is defined by adding additional high and low limits for *CV*s that are normally higher and lower than set ranges. When the current value of one *CV* violates these limits, the controller temporarily gives up controlling this *CV* while still controlling the other *CV*s that stay within in the specified limits. A simplified illustration in **Fig. 5** shows how this method works in the kick situation. When BHP increases beyond the prioritizing limit, MPC immediately turns off the BHP *CV* and fully focuses on the Flow Balance *CV*. After mitigating the gas influx, the new set range is set based on the stabilized BHP plus a safety margin. Then, the controller automatically turns on the BHP *CV* again by having a current value within the prioritizing limit.

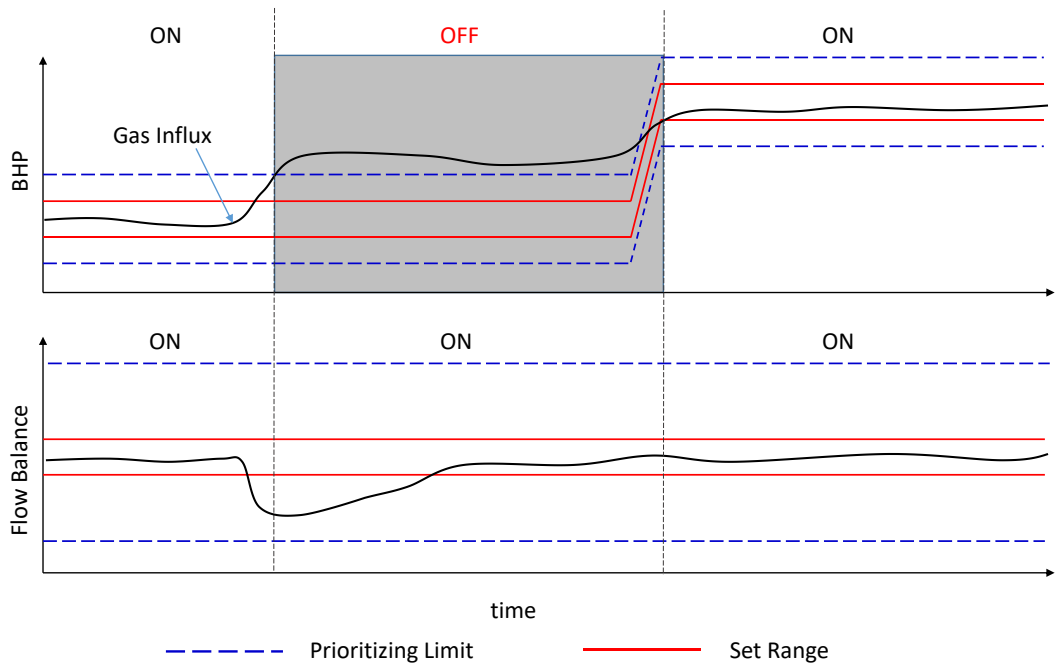


Fig. 5 — Illustration of prioritizing function for kick attenuation

Result and Discussion

The simulation results of the three previously described scenarios are detailed in this section. **Fig. 6** shows the result of normal drilling operation. The servo control performance is tested for both (a) PID and (b) NMPC. The SISO configuration of PID allows the controller to move one *MV* at a time. The choke valve opening (z_c) is a single *MV* for the PID controller while NMPC adjusts choke valve opening (z_c) and mud pump flowrate (q_p) simultaneously. In order to test the performance for a severe situation, greater changes in the set point than typical operation are demonstrated. The PID controller cannot reach the set point changes, even though the choke valve moves are more aggressive and cover the full range of the valve opening (0 – 100%). This result shows that the operation is limited into a narrow pressure range with adjustments only to the choke valve opening. Improved performance is demonstrated by using the

mud pump flowrate to add or remove the pump head pressure in the wellbore pressure. In the NMPC result, BHP quickly follows the set point changes by coordinating adjustments to the two *MV*s.

Fig. 7 shows the results of the pipe connection procedure. Unlike the normal drilling scenario, the pipe connection procedure covers a wider operation range by ramping down and up the main mud pump from the normal operation range to zero and back again. In this case, the nonlinearity problems are more evident than in a normal drilling operation. Similar to the normal operation case, the PID controller fails to maintain the BHP within an acceptable range (a). Although it fully closes the choke opening while ramping down the mud pump flowrate, it is not sufficient to compensate for the mud pump head pressure loss. For this specific case, MPD employs the back pressure pump to exert additional pressure by maintaining the mud circulation flow through the choke valve. The back pressure pump is included as an *MV* in the NMPC configuration. Thus, the back pressure pump and choke valve move together and successfully maintain the BHP within ± 1 bar deviation (b). Furthermore, when the mud pump flowrate *MV* is set to receive a ramp input, NMPC automatically considers it as a process disturbance variable, *DV*. The NMPC controller includes the change of the *DV* in the prediction and control calculation. This gives

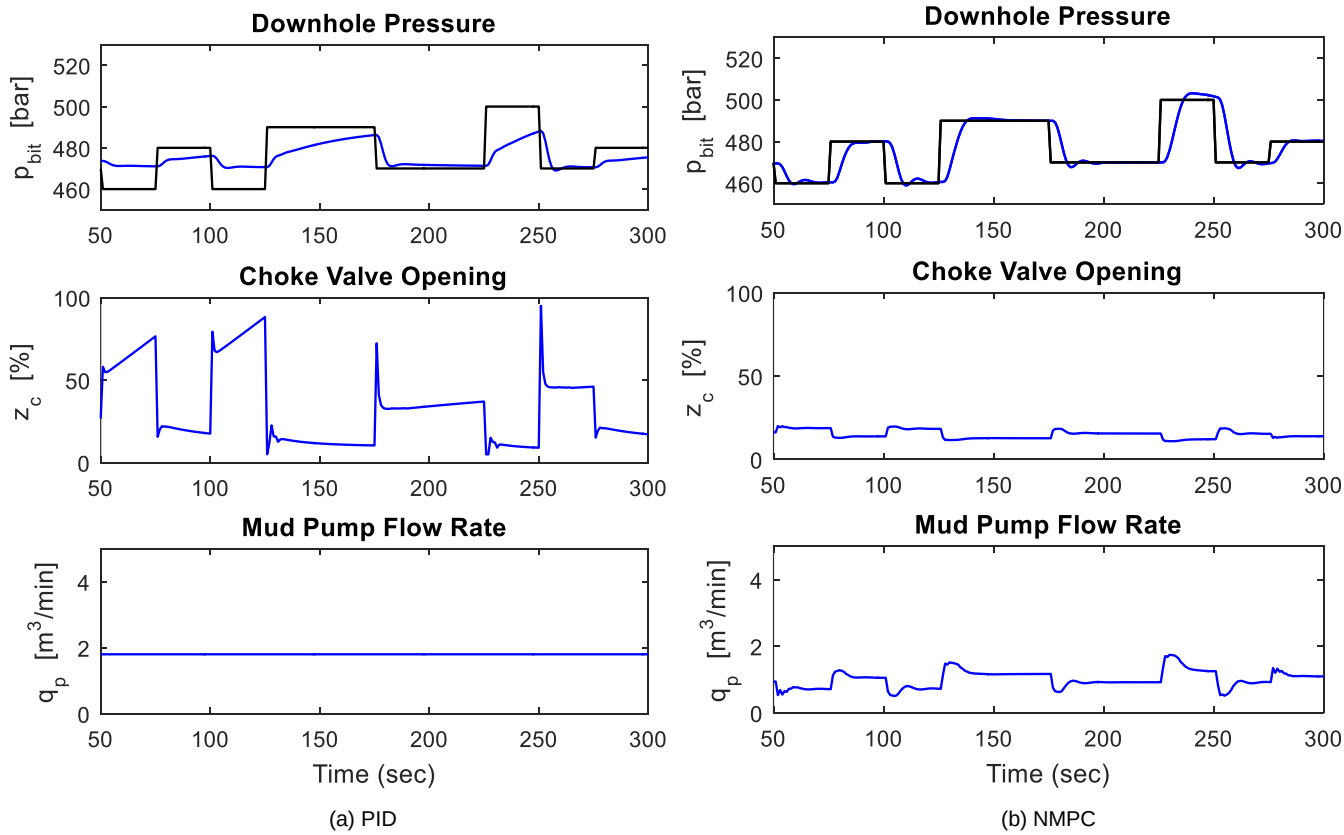


Fig. 6 — Comparison of BHP control performance during normal drilling

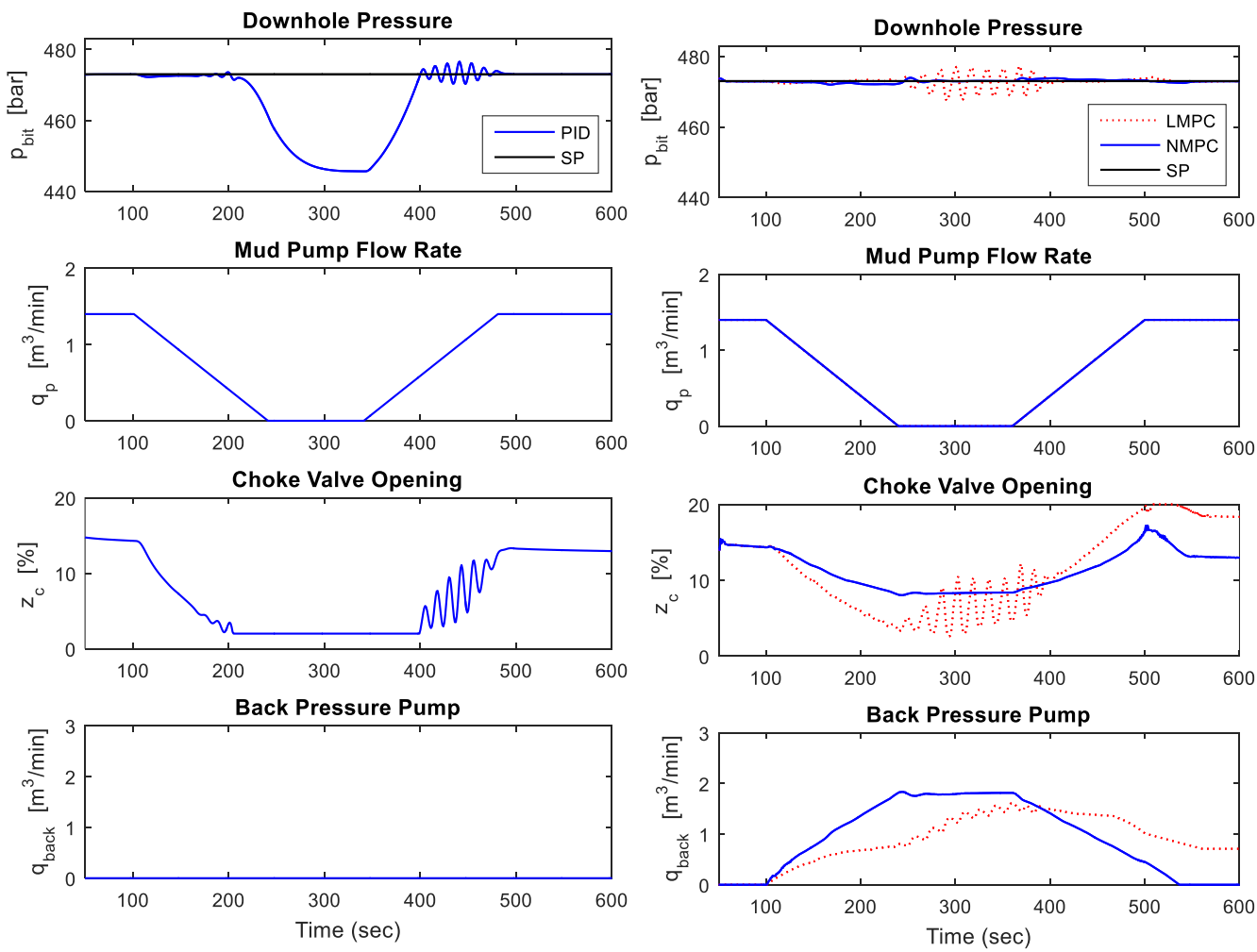
feedforward information that is unavailable to controllers that rely solely on feedback control. To validate nonlinear control of the Hammerstein-Weiner NMPC, the pure LMPC control results are compared with the NMPC results in the same plot (b). The LMPC, not including the Hammerstein-Weiner nonlinearity block, shows severe oscillation on both the *CV* and *MV*s when the mud pump flowrate reaches zero. On the contrary, the NMPC shows the appropriate control performance covering the process nonlinearity with the static nonlinear blocks.

Fig. 8 shows the kick attenuation performance of NMPC. The *CV*s and WeMod output are shown in (a) and *MV*s of NMPC are displayed in (b). The additional *CV*, flow balance (q_{bal}), is added to the existing

control matrix that already has BHP as a main *CV* for normal drilling and pipe connection. Both *CV*s are turned on at the beginning of the simulation. The control set ranges of the BHP and flow balance are set to ±1 of 466 bar and ±0.01 of 0 m^3/min, respectively. New prioritizing limits are applied to both *CV*s, with the limits for the BHP being relatively narrower than those of the flow balance, as summarized below.

Control set range for p_{bit} = set point for p_{bit} ± 1 bar
Control set range for q_{bal} = set point for q_{bal} ± 0.01 m^3/min
Prioritizing limits for p_{bit} = set point for p_{bit} ± 3 bar
Prioritizing limits for q_{bal} = set point for q_{bal} ± 0.5 m^3/min

where, set point for p_{bit} = 466 bar
set point for q_{bal} = 0 m^3/min

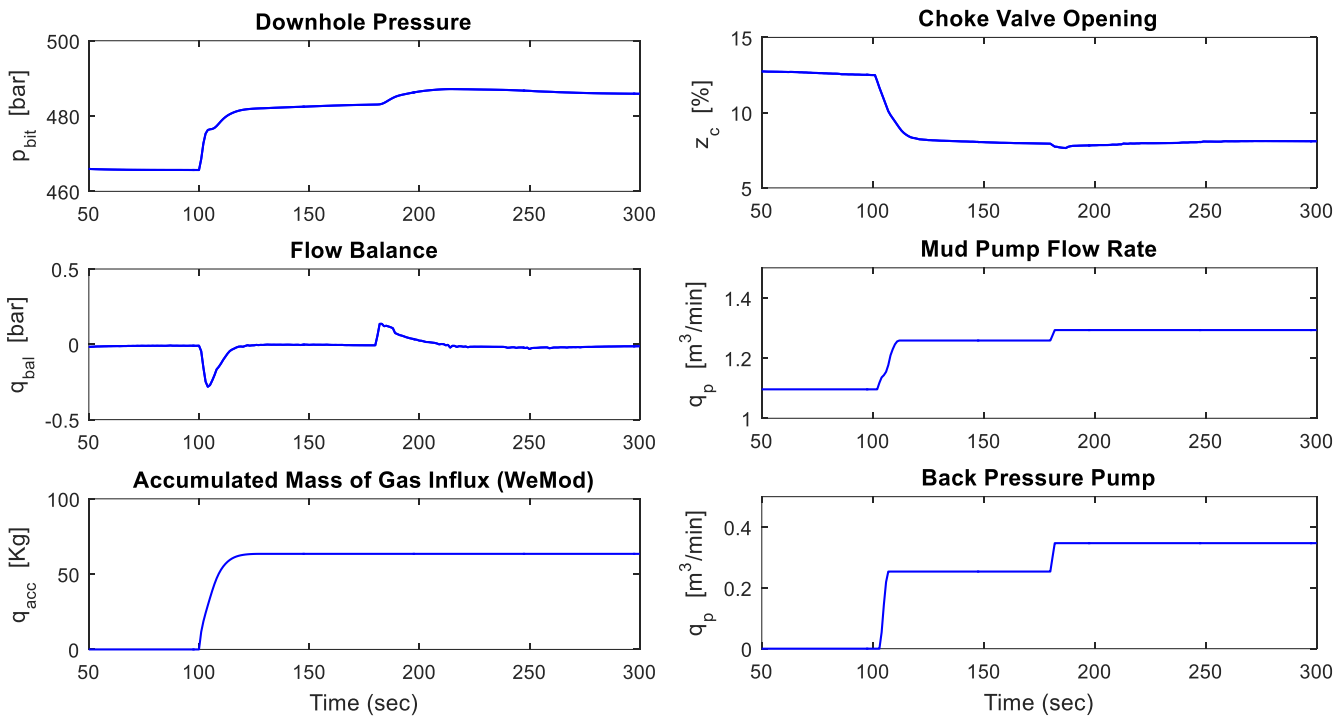


(a) PID (b) LMPC and NMPC

Fig. 7 — Comparison of BHP control performance during pipe connection procedure

Both of the *CV*s (flow balance and BHP) fluctuate as the gas influx starts at 100 seconds. The controller immediately turns off the BHP control letting it increase and stabilize at a new balance condition while attenuating the gas influx with the other *CV*, flow balance. After the gas influx starts, the BHP steeply increases and goes above the prioritizing limits, while the flow balance is still within prioritizing limits. The controller logic prioritizes flow balance control over BHP control to attenuate the kick. In the results,

the controller closes the choke valve and increases both the main mud pump and the back pressure pump, which is anticipated in kick attenuation. These control actions efficiently block the gas migration and increase the wellbore pressure to balance to the new reservoir pressure. Approximately one minute after the kick occurs, BHP is stabilized at 481 bar, stopping the amount of total gas influx at 60 kg. At 180 seconds, the set point of the BHP is adjusted based on the current pressure with an additional safety margin. The BHP is now placed within the prioritizing limits and turned on for future pressure control.



(a) CVs and WeMod output (b) MVs

Fig. 8 — kick attenuation performance of NMPC

Conclusions

This study proposes an advanced NMPC control algorithm for MPD automation of BHP and flow balance control. The Hammerstein-Wiener based NMPC shows a superior control performance to a conventional PID controller. A number of advantages of NMPC are discussed and validated with common operation scenarios. The proposed method assumes that the bottom hole pressure is measurable by WDP telemetry. The proposed method improves the control reliablity by eliminating uncertainties of predictive BHP estimation. By adjusting multiple *MV*s simultaneously the control performance is significantly improved for normal drilling, pipe stand connections, and in kick attentuation. For the kick attenuation scenario, adding the additional *CV* and prioritizing limits combines flow balance control and utilizes BHP control when there is no significant flow imbalance.

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