An Intelligent Control Approach for Oil Drilling Processes

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Abstract

The paper presents an intelligent control and optimization framework for managed pressure drilling systems. The nonlinear drilling process model was configured in a closed-loop feedback control framework to optimize the oil drilling process performance. Two main process components, namely, the mud pump flow rate and the differential flow rate of the backpressure pump and the choke, are assumed to be the control inputs while the process down hole pressure rate is treated as the process output. The control, optimization and automation of the drilling process are investigated by designing an intelligent fuzzy logic controller in a tracking problem for real-time implementation, by utilizing the closed loop system tracking error and the error rate as the controller inputs and by generating incremental changes for the two process inputs.

Although the proposed control system framework is inherently nonlinear due to the nonlinear process model and the nonlinear intelligent control, the process control input and output parameters have been successfully achieved. The proposed control framework simulation results clearly illustrate that the managed pressure drilling process can be optimized as a closed loop control tracking problem, effectively removing the need for complex controller design and allowing real-time implementation in manufacturing operations in operator support systems.

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I. INTRODUCTION

Oil drilling systems have recently generated considerable research focus on various control system approaches to improve overall system performance due to implied benefits in terms of performance, economical cost, safety...
advancements, and sustainability [1]. The Managed Pressure Drilling (MPD) approach is an adaptive drilling process to control the annular downhole pressure throughout the bore well continuously. Although the MPD approach reduces a number of drilling-related problems such as lost circulation, stuck pipe, well bore instability, well-control incidents [2] and improves the economics of drilling operations, deeper-water drilling wells amplify the nature of drilling problems, implying a need for advanced theoretical and practical tools. Based on the practical results [3, 4, 5], an intelligent nonlinear feedback control framework with a fuzzy logic controller can overcome a number of MPD problems, improving the process performance, efficiency and real-time implementation capability.

Intelligent closed loop control frameworks with fuzzy logic controllers provide a viable option to circumvent nonlinear model complexities in real-time implementations. The fuzzy logic concept [6] formulates the human brain inference logic in mathematical structures via fuzzy sets and rules, and generates desired performance outputs especially when mathematical model input-output relationships are vague, highly nonlinear, or likely yielding intractable solutions [3]. Intelligent controllers have been shown to produce acceptable results in a number of control and optimization applications, such as a damage mitigation optimization system [3], an arc welding process that is partially controlled by a fuzzy logic controller [7], a laser quality control with a fuzzy proportional-integral-derivative control system [8], or an intelligent hybrid fuzzy-PI controller in a drilling rig with performance and stability improvements [9].

This research proposes a closed loop nonlinear control system framework for managed pressure oil drilling processes, by designing a fuzzy logic controller in a tracking problem and by manipulating the implied MPD process input variables to achieve the desired MPD process output, i.e., the annular downhole pressure in well bores, for real-time operations. The proposed framework has been proven effective, based on the simulation results. Section I introduces the MPD systems and intelligent control approaches, The baseline nonlinear MPD process model and associated system operation are reviewed in Section II. The closed loop control system framework, MPD implementation, and numerical simulations are presented in Section III while Section IV concludes and suggests possible future work.

II. BACKGROUND

The managed pressure drilling system nonlinear model and process control operation is reviewed [10] in terms of control-related system approach.

![Fig.1. The managed pressure drilling system block diagram.](image)

The practical MPD system, shown in Fig. 1, includes two inputs, namely, the differential of the backpressure and choke flow rates and the mud pump flow rate, and one output, the annular downhole pressure rate, and follows

\[ \dot{P}_p = a_1(q_{pump} - q_{bit}) \]

where \( P_p \) denotes the inlet mud pump pressure (bar), \( q_{pump} \) indicates the mud pump flow rate (m³/sec) and \( q_{bit} \) represents the flow rate through the drill bit (m³/sec) while the \( a_1 \) coefficient is defined as \( \frac{\beta_d}{v_d} \), where \( \beta_d \) is the bulk modulus of the drill string and \( v_d \) is the volume of drill string. The MPD process also includes the outlet choke pressure \( P_c \) (bar) dynamics as

\[ \dot{P}_c = a_5 \left( q_{res} + q_{bit} + u + v_a \right) \]

where \( q_{res} \) is the reservoir influx rate (m³/sec), \( v_a \) is the annulus volume (m³), \( a_5 \) is equal to the bulk modulus of the annulus (\( \beta_a \)), and the differential control input \( u \) is given as

\[ u = q_{back} - q_{choke} \]

where \( q_{back} \) denotes the backpressure pump flow rate (m³/sec) and \( q_{choke} \) denotes the choke flow rate (m³/sec).

Using Eqns. 1-2, the flow rate through the drill bit \( q_{bit} \) nonlinear dynamics is given as
where $h_{bit}$ denotes the vertical depth of the bit, and the coefficients are given as

$$\dot{q}_{bit} + a_2 (P_b + P_c) + a_3 q_{bit}^2 + \theta (q_{bit} + q_{res})^2 + a_4 h_{bit}$$

where $M_d$ is the density per meter of the drill string, $M_a$ is the density per meter of the annulus, $F_d$ is the friction factor of the drill string, $F_a$ is the friction factor of the annulus, $\rho_d$ is the density of the drill string, $\rho_a$ is the density of the annulus and $g$ is the gravitational acceleration. These equations are derived under the assumptions that $q_{res}$ is a constant value, i.e., usually an unknown disturbance, and $q_{bit} > 0$, $q_{bit} + q_{res} > 0$. Finally, the nonlinear annular down hole pressure dynamics is given as

$$P_{bit} + M_a \dot{q}_{bit} + F_a (q_{bit} + q_{res})^2 + \rho_a g h_{bit}$$

III. INTELLIGENT CONTROL SYSTEM DESIGN FRAMEWORK

The MPD process nonlinear model in Eqn. 4, as shown in Fig. 2-a, is used to design an intelligent controller in a closed-loop unity feedback control system, in terms of a tracking problem as shown in Fig. 2-b, to achieve desired annular down hole pressure ($P_{bit}$) values. The drilling process optimization is accomplished by considering different down hole pressure reference inputs to reflect practical conditions and by determining the required MPD process input parameters.

The intelligent controller rules, variables, and associated membership functions were designed by using the MPD process principles, obtained by studying its nonlinear model in Eqns. 1-4 for a number of different reference inputs. The fuzzy logic controller included two inputs, i.e., the error and the error rate of the feedback control system, with the error rate determined via the $(z - 1)/z$ discrete-time transfer function, and generated two outputs, namely, the differential control input $u$ and the mud pump flow rate, as shown in Fig. 3.
The controller error and error rate input variable fuzzifications were done by using nine and three membership functions, respectively, with different types, with the final membership function characteristics were determined after a number of trials for the optimal system performance, as shown in Fig. 4. The fuzzy sets associated with each membership function are the same for the inputs and outputs, i.e., n4, n3, n2, n1 denotes different negative levels, p4, p3, p2, p1 denotes different positive levels and z denotes zero for each variable.

![Fig. 4. The fuzzy logic controller input fuzzy sets and membership functions; (a) The error and (b) The error rate.](image)

The incremental variations in two MPD process inputs were used to determine the fuzzy logic controller outputs, by performing fuzzification of the variables with nine membership functions with different types, as shown in Fig. 5. Assuming each current step MPD process input is Uk and the fuzzy logic controller output is ΔUk, then the MPD system next step input is calculated as Uk+1 = Uk + ΔUk. The incremental change amounts present a dilemma during the controller design such that larger increment amounts likely generate overshoots or highly oscillatory responses while smaller increment amounts likely result in slow output responses and larger settling times.

![Fig. 5. The fuzzy logic controller output fuzzy sets and membership functions; (a) The differential control input, and (b) The mud pump flow rate.](image)

The resultant inference rules, shown in Fig. 6, for the fuzzy logic controller were developed by studying the nonlinear MPD model responses for different reference inputs. The feedback closed loop system and the fuzzy logic controller performances likely increase as more properly developed inference rules are included. However, development and completeness of efficient inference rules may also complicate the controller design as more rules will start interfering with the existing rules. The rule viewer option of the fuzzy logic controller development positively supports the rule development efforts by providing a visual controller operation to investigate the impact of each additional rule, with the design goal of a sufficient number of rules ensuring desired closed loop system operations.
The feedback control system incremental output variations assume no MPD process input and output constraints. Therefore, hard limiter blocks were used on each physical MPD process input variable path to ensure practical impact of the feedback control system results. The differential input hard limiter lower and upper bounds were set to -0.01 and 0.01, respectively, i.e., the differential input variable was allowed to change between the bounds while the same variable is limited to the -0.01 for values smaller than the lower bound and 0.01 for values larger than the higher bound. The negative values indicate the relative operation of the backpressure pump and choke rates. Similarly, the mud pump flow rate hard limiter lower and upper bounds were set to 0 and 0.01, respectively, in compliance with practical considerations. Also, the MPD process continuous-time model is interfaced with the discrete-time fuzzy logic controller via zero-order holder blocks with 1 second sampling time.

The Matlab Fuzzy Logic toolbox [11] was used to verify the proposed framework simulation performance with the initial conditions of \( P_p(0) = 120 \text{ bar} \), \( P_c(0) = 70 \text{ bar} \), \( q_{bit}(0) = 0.014 \text{ m}^3/\text{sec} \) and with the coefficients in proper units given in Table. 1.

| \( \beta_a = \beta_d = 14000 \) | \( \nu_a = 96.1 \) | \( M_a = 1700 \) |
| \( \nu_d = 28.3 \) | \( M_d = 5700 \) | \( F_a = 20800 \) | \( h_{bit} = 2000 \) | \( v_{a} = \rho_d = 0.0125 \) | \( q_{res} = 0.001 \) |

The fuzzy logic controller performance in the feedback control system configuration in Fig. 2-b has been studied for a variety of step reference changes and the corresponding illustrative system performance is given in Fig. 6 for two different operating conditions, where the desired annular down hole pressure is achieved for the MPD process output within acceptable settling time values. The attempts to minimize the settling time or to improve the overall response via different membership function values and types generated either comparable performance achievements or unstable system responses for the nonlinear control system.

![Fig. 6. The fuzzy logic controller inference rules.](image-url)

The MPD process input variables were also studied under linear and saturation type variable operations in the closed loop control system with the fuzzy logic controller. Fig. 8-a illustrates the implied fuzzy logic controller outputs for each MPD process input while Fig. 8-b presents the MPD process practical control inputs that were actually applied to the MPD process nonlinear model. Although the linear type variable operation requires hypothetical negative variations on the MPD process control inputs, the hardlimiters on the MPD control input paths ensure practical values for real-life MPD processes.
IV. CONCLUSION

A managed pressure drilling process control and optimization framework has been successfully demonstrated by using a closed loop control system with an intelligent fuzzy logic controller. The simulation results have proven the efficiency of the proposed framework in terms of practical significance, nonlinear optimization, and real-time implementation for operator support.

The optimization framework of the managed pressure drilling process can also be investigated under possible drilling process time delays for the overall system performance.

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