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Full-course drilling model for well monitoring and stochastic estimation of kick

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ABSTRACT

Application of model-based estimation techniques to kick detection come with constraints imposed on the structure of the mathematical model by stochastic estimation algorithms as well as the limited number of flow-line measurements typically available in most drilling operations. This, along with high computational cost of numerical models call for low to medium order deterministic models that still capture the dominant effects of fluid flow during drilling. A built-for-purpose single phase deterministic model for conventional drilling is presented. The model development is the first step in a two-step process of real-time early kick detection using stochastic estimation techniques. The model is developed using lumped parameter modeling afforded by bond graph modeling technique. Aside a hydraulic model for the wellbore, well-formation interactions that give rise to kicks, lost circulation, and wellbore breathing are also modeled and coupled. This holistic modeling approach provides a compact set of low order equations which makes stochastic estimation feasible, and well monitoring easier so that, for example, wellbore breathing is not mistaken for kicks, leading to unnecessary non-productive time and possibly inducing kicks due to needless well control actions undertaken. Lumped well parameters are calibrated with an optimization tool, and the model is validated using historical data from a conventionally drilled, onshore well.

1. Introduction

The field of well flow and kick modeling has been dominated by numerical models based on mass, momentum, and energy conservation laws in distributed parameter forms. These complex, high fidelity models feature multi-phase unsteady flow equations and an elaborate description of flow regimes. They provide the capability to track kick gas migration from bottomhole to surface and are deployed as commercial simulators for flow assurance, well planning, and after-the-fact analysis of well control issues (Bendiksen et al., 1991; Danielson et al., 2011).

More practical multiphase flow models for drilling applications are also derived from first principles, although the energy equation may be discarded due to slow temperature dynamics. Simplified closure relationships for density, friction pressure loss, influx rate, and gas dissolution rate, among others, are used (Rommetveit and Blyberg, 1989; Starrett et al., 1990). In their deployment as well monitoring tools, model results are compared with well sensor data and discrepancies are marked as an indication of anomalies like kicks (Rommetveit et al., 2004). Though they are sourced from fundamental conservation laws, these models still share the same limitations that all deterministic models have (Maybeck, 1979):

1. Mathematical models are approximations depicting only the dominant effects of a process. Hence no such model is perfect and sources of uncertainty exist.
2. Disturbances are present in all systems and these can neither be modeled deterministically nor controlled.
3. Sensors used to measure system response are themselves imprecise. They introduce their own dynamics and distortions to readings, and data is often corrupted by noise. Also, in some cases, sensors cannot be devised to measure quantities of interest.

These limitations inform the use of well sensor data to continuously update model parameters using optimization routines. Where model-based estimation techniques are used in conjunction with these models, they are applied for reservoir characterization using Ensemble Kalman filters (EnKF) (Vefring et al., 2003), or tuning of flow model and pressure loss parameters using unscented Kalman filters (UKF) (Iversen et al., 2006). However, there is usually insufficient topside and downhole sensor data to adequately calibrate all distributed model parameters

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along the wellbore, hence overall accuracy of models is still impacted (Kaasa et al., 2011).

Stochastic estimation operates to minimize the limitations of deterministic models. They go beyond comparing deterministic model predictions with sensor data. Well observations are assimilated into model predictions in order to update observed state variables and provide estimates for unobserved state variables, all while minimizing error. Model and measurement uncertainties are also accounted for in the process.

To apply stochastic estimation in dynamic kick prediction, well state variables have to be predicted at each time step prior to inferring posterior estimates from observations. The use of distributed parameter models to describe well behavior mean that PDEs first have to be discretized, yielding high dimensional discrete systems which are expensive to compute. This highlights two limitations of using PDE models for model-based estimation. Firstly, the order of available measurements have to match the order of the predictive model in order for the system to be observable and controllable (Anderson and Moore, 1989). High order distributed models mean that sensors have to be installed along the entire flow line. This is an expensive undertaking and very few wells use the technology. Hence the application has had to rely on a less constraining criteria of detectability for implementation where only a small number of observable states are estimated (Nikoofard et al., 2015). Secondly, where Sequential Monte Carlo techniques are to be used for estimation, the computation cost in addition to numerical model prediction could be prohibitive and impractical especially for real-time applications like kick detection during drilling. Hence simpler, ODE models are desirable where the application indicates that multiphase flow dynamics can be ignored without excessive loss of accuracy.

Kaasa et al. (2011) developed a low order, single phase model for managed pressure drilling (MPD) applications. The model has also found use in surge and swab estimation and control during tripping (Gjerstad et al., 2013). In Ojinnaka et al. (2016), a single-phase drilling model suitable for model-based estimation was described. The model was coupled with the linear Kalman filter to predict kicks. The use of Kalman filter for state estimation means that nonlinearities in well flow and well-reservoir interaction models have to be linearized. A drawback of doing this is that first order truncation of the series expansion leads to some loss of system information as the prior probability density function and likelihood functions are propagated in time (Maybeck, 1979). Accuracy of estimates is thus impacted. A linear system also means that applicability is limited to drilling ahead activity only, when the pumps are on and inflow rate is steady.

The focal point of the present paper is to apply bond graph technique to develop a full course, low order deterministic model for conventional drilling suitable for application in real time kick detection using nonlinear stochastic estimation techniques. The model accounts for pumps-on drilling ahead and pumps-off stationary well situations, as well as wellbore breathing and mild lost circulation. As a deviation from other kick models, a submodel for the pore pressure is coupled. Real-time pressure difference between reservoir and openhole drives influx into the wellbore. Hence, rather than use predetermined pore pressure estimates which are uncertain and become inaccurate if drilling ahead encounters unpredicted overpressured zones, a pore pressure model outputs estimates at each time step during stochastic estimation. Subsequently, influx rate or lost circulation can be calculated using established pore pressure-wellbore pressure relationship models.

2. Lumped-parameter modeling using bond graphs

A bond graph is a tool used to depict physical systems graphically, from which dynamic equations can be extracted. Subsystem are represented as equal power bonds each one carrying a power conjugate (effort and flow) that portray instantaneous energy storage and flows in dynamic systems. The use of power bonds mean all system types can be modeled, be they hydraulic (pressure × flowrate), mechanical (force × velocity), electrical (current × voltage), thermal or chemical systems. Energy transfer between subsystems occur at junction elements which are modeled such that mass and momentum are conserved, and dynamic equations are easy to extract. A set of bond graph elements are used to account for energy sources and sinks, energy storage, dissipation, and flow:

1. Source elements: both externally-defined efforts (S_E) and flows (S_F), e.g. mud pump.
2. Capacitive "C" elements: capable of storing potential energy, e.g. volumes that store compressible fluids such as mud pit, drillstring, and annulus.
3. Inertial "I" elements: capable of storing kinetic energy, e.g. fluid inertia.
4. Resistive "R" elements: capable of dissipating energy, e.g. pressure loss during fluid flow
5. Transformers and gyrators: idealized power coupling elements which do not themselves create, store nor dissipate energy but losslessly transfer energy from one physical domain to another, e.g. from hydraulic to mechanical energy.
6. Junction elements: used to represent constraints for energy transfer among subsystems, such as conservation of mass or momentum in equal effort (0-junction) and equal flow (1-junction) scenarios.

Constitutive relationships between system parameters and variables lead to lumped parameters for inertia, capacitance, and resistance which direct and meter energy flow between system components. Lumped parameter modeling provides a means of transforming spatially distributed, infinite dimension systems into discrete time, finite dimension representations. Using bond graphs, distributed parameter systems like flow in long hydraulic lines are represented as transmission lines where the flow line is divided into any convenient number of finite lumps with each lump exhibiting compliance, inertia, and dissipation characteristics in order to model the dominant effects of fluid flow. The finite lumps are similar to discretization in partial differential equations. Aside from simplicity and inherent stability of the model equations, lumped parameter modeling means that flow systems can be calibrated more accurately even with limited measurement signals from a well. Karnopp et al. (2012) provides an extended description of bond graph modeling.

2.1. Model structure

The model is specifically built for well monitoring and early kick detection using stochastic estimation techniques. Since system observability is a constraint in model-based estimation, the small number of flow-related measurements available in most drilling operations dictate a low order system except where wired drillpipe telemetry data is available.

Hence, the wellbore is divided into three sections: one drillstring and two annulus sections consisting of a cased hole and an openhole. As with all flow models, pressure and flow rate changes with time are important variables to track. For the two annulus sections, pressure momentum defines the well state and outflow rate at the top of the annulus accounts for any mass transfer into or out of the wellbore from its interaction with the reservoir. Fluid compressibility is captured in a change in volume relationship with well pressure. Given the assumed unavailability of flow line data, and in order to more accurately estimate the pore pressure through its relationship with the pump pressure, mud compressibility in the drillstring is not modeled and the flow source results in a derivative causality for the change in pressure momentum in the drillstring, $\dot{\Gamma}_{ds}$, which is subsequently ignored.

A Cartesian reference frame is fixed at the rotary kelly bushing (RKB) from which the drill bit and true vertical depth (TVD) of the bottomhole is tracked as drilling progresses in the axial direction. Any kick or lost circulation is assumed to occur at the bottomhole. This is where an influx/lost circulation model is coupled to the wellbore model. A