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Review of two-phase flow models for control and estimation

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ABSTRACT

Most model-based control and estimation techniques put limitations on the structure and complexity of the models to which they are applied. This has motivated the development of simplified models of gas-liquid two-phase flow for control and estimation applications. This paper reviews the literature for such models with a focus on applications from the field of drilling. The models are categorized in terms of complexity and the physical interpretation of the simplifications employed. A simulation study is used to evaluate their ability to qualitatively represent dynamics of 3 different gas-liquid scenarios encountered in drilling, based on which conclusions are drawn.

1. Introduction

Drilling for hydrocarbons is the process of creating a well-bore, sometimes extending several thousand meters into the ground, until it reaches an oil or gas reservoir (Fig. 1). There is a multitude of risks and challenges associated with this process, including controlling the distributed pressure in the well within the constraints imposed by the operation.

Dealing with these challenges has entailed an increasing drive for automation in many aspects of drilling (Godhavn, 2011; Thorogood, Aldred, Florence, & Iversen, 2010). Simultaneously, a goal of improved drilling efficiency is pursued through reducing non-productive time, optimizing operations, and detecting and avoiding incidents before adverse consequences occur (Cayeux, Daireaux, Dvergsnes, & Florence, 2014). The trend for drilling deeper and more complex wells (Lukawski et al., 2014) is also a driver for automation as an enabling technology, allowing for continued exploration of difficult and mature reservoirs.

Following the demand of the drilling industry, high fidelity simulators of the drilling process have been developed. Applications of these include training of drilling personnel and real time decision support (Petersen, Rommetveit, Bjorkevoll, & Froyen, 2008; Rommetveit et al., 2004). At the same time, automated control systems for controlling various aspects of the drilling process have been developed and are gradually being accepted by the industry (Santos et al., 2007).

Modern approaches to process monitoring, optimization and control promise to enhance robustness and performance of such automation through the merger of process knowledge encoded in mathematical models with real-time measurements from the process. By intelligently combining predictions from the mathematical model with information from multiple sensors one can estimate unmeasured quantities, optimize automatic control procedures, predict future behavior, and plan countermeasures for unwanted incidents. Such design techniques, often referred to as model based estimation and control (Anderson & Moore, 1990; Åström & Murray, 2010), require a mathematical model with the right balance between complexity and fidelity: i.e. the complexity must be limited to facilitate the use of established mathematical analysis and design techniques, while the qualitative response of the process is retained.

Models that strike the right balance between complexity and fidelity are sometimes referred to as fit-for-purpose models, and have been employed in control (Stamnes, Aamo, & Kaasa, 2011a) and monitoring (Willersrud, 2015) of drilling processes in one-phase flow regimes. Obtaining such simplified models becomes significantly more difficult for gas-liquid two-phase dynamics due to the significant complexity and distributed nature of multiphase pipe-flow (Aarsnes, Di Meglio, Evje, & Aamo, 2014; Aarsnes, Di Meglio, Graham, & Aamo, 2016). This makes the reduction to fit-for-purpose models for scenarios such as gas-kick incidents, and underbalanced operations, challenging.

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Nomenclature

c	Sound speed
$m = \alpha_\ell \rho_\ell$	Liquid mass
$n = \alpha_g \rho_g$	Gas mass
q	Volumetric flow-rate
t	Time, independent variable
v	Velocity
v_∞	Slip relation drift velocity
w	Mass flow-rate
x	Position, independent variable
C_0	Slip relation profile parameter
F	Frictional pressure loss
G	Gravitational pressure loss
P	Pressure
T	Temperature
V	Volume
α	Volume fraction
β	Bulk modulus
γ	Adiabatic index
ρ	Density
μ	Chemical potential
$\mathcal{J}, \mathcal{K}, \mathcal{M}, \mathcal{H}$	Relaxation coefficients

Subscripts

a	Lumped annulus parameter
c	At or exiting through the choke
d	Lumped drill string parameter
i	Interface
M	Mixture
ℓ	Liquid phase
g	Gas phase
bit	Entering the annulus from the drill string
inj	Injected into the drill string
res	Entering the annulus from the reservoir

Abbreviations

DFM	Drift Flux Model
BHP	Bottom-Hole Pressure: $p_{bh} = P(0)$
LOL-model	Low Order Lumped-model
MPD	Managed Pressure Drilling
ODE	Ordinary Differential Equation
PDE	Partial Differential Equation
UBD	Under-Balanced Drilling
WHP	Well-Head Pressure: $p_a = P(L)$

Consequently, several different approaches have been suggested in the literature, ranging from using complicated high-order numerical schemes with advanced multiphase-flow models to simplified low-order or black-box step response representations. The present paper presents a review of these models used for designing control and estimation/monitoring algorithms of gas-liquid two-phase dynamics encountered in drilling. The survey will focus on the models used and not the methods in themselves.

1.1. Components of a simulation model

To structure the following discussion, it is useful to identify the distinct components which make up a complete simulation model. The three components are *Mathematical structure, Closure Relations* and the *Numerical Scheme* and they are summarized in Table 1.

The complexity of a model is mainly determined by its *mathematical structure*. This is the type and number of dynamical equations needed to describe the model. Determining the mathematical structure of the model also determines, crucially in our case, the mathematical tools and the model based estimation and control algorithms which can be employed with it.

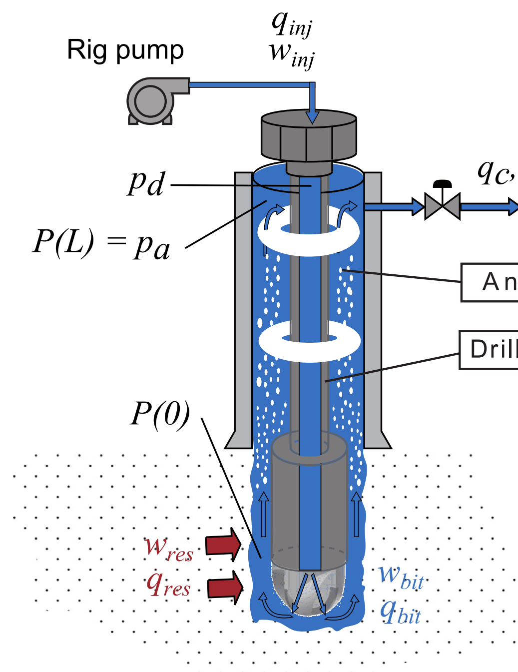

Fig. 1. Schematic of the system under consideration.

Table 1
The three components of a complete simulation model.

Mathematical structure	Closure relations	Numerical scheme
• PDE or ODE	• Slip law	• Numerical accuracy
• Hyperbolic or Parabolic PDE	• Equation of state	• Numerical stability/ robustness
• Number of equations	• Frictional pressure loss	• Implementation complexity
• Stiffness	• Other source terms	• Solution speed

The *closure relations* that are used will necessarily depend on the mathematical structure of the model. When a model is simplified, the closure relations will often also have to be modified to accommodate for the simplification, typically in such a way as to retain the steady state profile. Closure relations can also be chosen and *tuned* based on experiments or measurements, and consequently, given a mathematical structure, the accuracy of the model will mostly be determined by the value and form of the closure relations chosen.

The final component to a simulation model is the *numerical scheme*. This is the way the mathematical equations are approximated in order for them to be solved numerically. The solution procedures that can be utilized have varying degrees of accuracy and solution speeds. Additionally, they may differ in terms of numerical stability, robustness and complexity in implementation, which is of importance when employing the scheme for a model as part of a control or estimation algorithm.

1.2. A coarse classification and outline

To structure the paper we split the models found in the literature into the three broad categories according to their overarching mathematical structure.

1.2.1. High fidelity models:

This category encompasses models which are designed to be accurate and have a high degree of predictive power over a wide