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Joint Unscented Kalman Filter for State and Parameter Estimation in Managed Pressure Drilling

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***Abstract*— Drilling into offshore deep water, high-pressure high-temperature reservoirs is a very challenging process. The most important task in these drilling operations is to control bottomhole pressure. Many automatic control systems for drilling operations are based on models calculating wellbore pressure, flow and downhole hydraulics. Closed loop control systems, for example Managed Pressure Drilling, are examples of systems that may involve such real-time calculations. Therefore a high degree of accuracy in pressure and flow predictions is crucial to the performance of automatic drilling applications. In this paper the key uncertain model parameters and the bottom-hole pressure are estimated using joint unscented Kalman filter based on only available top-side measurements. The results of simulations show accurate estimation of the bottom-hole pressure and uncertain parameters, even in transient periods for example the scenario of pipe connection operations, where there is no available bottom-hole pressure measurement, and flow through the bit.**

I. INTRODUCTION

In drilling operations, drilling mud is pumped down the drill string and flows through the drill bit in the bottom of the well (see Figure 1). Then the mud flows up the annulus carrying cuttings out of the well. To avoid fracturing, collapse of the well, or influx of fluids surrounding the well, it is crucial to control the pressure in the open part of the annulus within a certain operating window. In conventional drilling, this is done by mixing a mud of appropriate density and adjusting mud pump flow-rates. In managed pressure drilling (MPD), the annulus is sealed and the mud exits through a controlled choke, allowing for faster and more precise control of the annular pressure. In automatic MPD systems, the choke is controlled by an automatic control system which manages the annular mud pressure to be within specified upper and lower limits. The variants of MPD, drilling automation, equipments and technology components can be found e.g. in [1]–[4]. Different aspects of modeling for MPD have been examined in the literature [5]–[7]. Estimation and control design in MPD has been investigated by several researchers so far [7]–[18]. Various challenges of modeling drilling systems for control and automation are discussed in [19].

In [7], [8], a Lyapunov based adaptive observer is designed to estimate uncertain friction and density in the annulus,

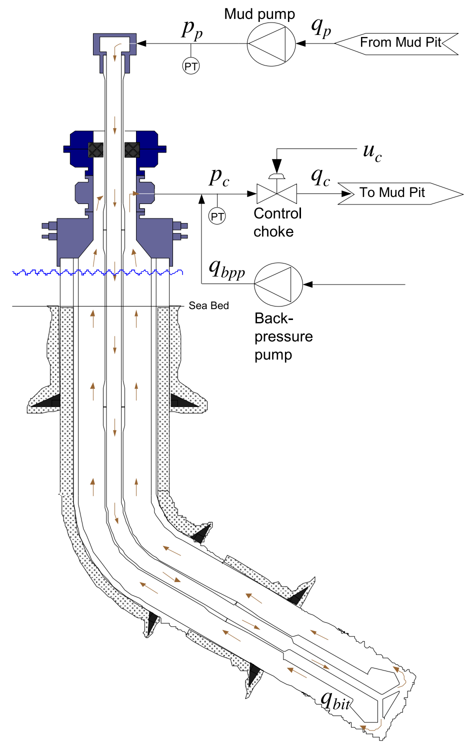

Fig. 1. Schematic of an MPD system, courtesy of Glenn-Ole Kaasa, Statoil.

and the bottomhole pressure in a well during drilling. In [20], an ensemble Kalman filter methodology was used to tune the uncertain parameters of a well-flow model in an underbalanced drilling operation. In [9], [21], friction calibration factors in the drillstring and annulus are tuned with an unscented Kalman filter technique using topside and bottom-hole pressure measurements. However in [21] in transient periods the friction factors used as calibration parameters suffered from undesired significant variations. Moreover, the data from the Measurement-While-Drilling (MWD) system is not typically available in situations with low or zero drilling fluid flow rate, e.g. during pipe connection procedures. This is due to the fact that the mud pulse telemetry system is powered by a mud flow turbine and requires a certain fluid flow rate to be in operation. In this paper a joint Unscented Kalamn Filter (UKF) is designed to simultaneously estimate the unmeasured states and unknown parameters in a managed pressure drilling system using only available topside measurements. The performance of the algorithm is tested for the case of normal drilling operations and also connection operations where there is no

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flow through the drill-string and borehole pressure reduces significantly.

The paper is organized as follows: In Section II, we present a hydraulic model based on mass and momentum balances that provides the governing equations for pressure and flow in the well in a managed pressure drilling operation. The additive unscented Kalman filter methodology in its matrix form is presented in Section III, and joint unscented Kalman filter for simultaneous state and paramter estimation is discussed in Section IV. Section V provides simulation results and conclusions are offered in Section VI.

II. Managed Pressure Drilling Dynamics

A. MPD model

The hydraulic model of an MPD system derived from mass and momentum balances can be written as

$$\frac{V_d}{\beta_d}\frac{\mathrm{d}p_p}{\mathrm{d}t} = q_p - q \tag{1}$$

$$\frac{V_a}{\beta_a}\frac{\mathrm{d}p_c}{\mathrm{d}t} = q + q_{bpp} - q_c \tag{2}$$

$$M\frac{\mathrm{d}q}{\mathrm{d}t} = p_p - p_c - F(q) \tag{3}$$

$$q_c = u_c K_c \mathrm{sign}(p_c - p_0)\sqrt{|p_c - p_0|} \tag{4}$$

$$p_{dh}(l) = p_c + F_a(q) + \rho g h_{TVD} \tag{5}$$

where p_p is mud-pump pressure, V_d and V_a are the volume of the drillstring and the annulus respectively, β_d and β_a are the effective bulk modulus, q_p is the pump flow, q is flow through the bit, q_{bpp} is the flow from the backpressure pump, q_c is the flow through the choke, p_c is the choke pressure, M is the integrated density per cross section over the flow path, $u_c \in [0,1]$ is the normalized valve opening, p_0 is the pressure downstream the choke and $K_c > 0$ is a lumped parameter depending on the density, the discharge coefficient and the cross-sectional area of the fully open valve opening, $F(q)$ is the steady-state frictional pressure drop along the entire flow path, p_{dh} is the downhole pressure, ρ is the density of drilling mud, g is the acceleration of gravity, h_{TVD} is the true vertical depth of the well, and $F_a(q)$ is the frictional pressure drop in the annulus. The flow rate through the choke, eq (4), is modeled by a standard orifice equation. Derivation of the model and the underlying assumptions are discussed in [7].

B. Uncertainty sources

Several components of the transient hydraulic model, (1)-(5), have significant uncertainties, such as

- Rheology and viscosity of drilling fluid. Most drilling fluids are non-Newtonian, i.e. with a nonlinear relation between shear stress and shear rate. Consequently, the viscosity will not be constant over a cross-sectional flow area. To measure the shear stress/shear rate relationship, the viscometer measurements must be correlated with the rheological model applied. However, information is limited and normally inadequate for a model of high accuracy, particularly for modern oil based muds. Also, viscosity may depend on pressure and temperature. Manual rheology measurements are normally performed periodically on the rig at atmospheric pressure and temperature of the mud in the pit. Thus, information on influences of temperature and pressure variations is missing, [9], [21], [22].
- Temperature distribution in the well. The temperature has an effect on both rheology and density of the mud [9], [21].
- Frictional pressure loss models for drill-pipe and annulus. The frictional pressure loss depends on the mean cross sectional velocity, drilling fluid viscosity, flow regime, the hydraulic diameter, and pipe roughness. The accuracy of all these derived parameters is questionable. Moreover, the Fanning friction factor is a function of Reynolds number where the Reynolds number is a function of the fluid viscosity for a characteristic diameter [7], [8], [21], [22].
- Pressure loss through the entire Bottom-hole Assembly (BHA) and bit. The BHA consists of many components of unknown geometry with different flow rates. Among other parameters it is very influenced by the flow regime in the well, whether it is laminar or turbulent [21].
- Effective bulk modulus. Because the degree of mechanical compliance of casing, pipe, hoses, and other components are uncertain and also it is impossible to predict the amount of gas pockets, bubbles, or breathing of the well, [7].
- Well geometry. It is often complex and partially unknown [21].

Therefore calibration is a vital part of any real-time hydraulics model to predict the downhole pressure with high accuracy. The temperature variations in a well affect the rheological properties of the drilling mud, and the frictional pressure losses are dependent on the viscosity of the mud. Here we consider an unknown scaling parameter, θ_1, for $F(q)$ in equation (3) as a calibration factor compensating for temperature, viscosity and frictional pressure loss uncertainties. Similarly, θ_2 is considered for calibrating the uncertainties in well geometry, affecting the volume in the annulus, and bulk modulus in equation (2).

III. UKF using the matrix form of UT

In this work we use joint unscented Kalman filter for state and parameter estimation in MPD system described by (1)-(5). The issue of detectability of the system is not treated here, since it is implicit in the Lyapunov-based observer design carried out for the same model in [8]. Unscented Kalman Filter (UKF), in comparison to the Extended Kalman Filter (EKF), uses the nonlinear dynamic equations directly instead of linearizing it. Therefore it can accommodate a large degree of complexity in the underlying models. Moreover, the UKF has the same computational complexity as EKF. It was founded on the idea that it should be easier to approximate a probability distribution than an arbitrary nonlinear function [23]. Consult references [23], [24] for a more detailed description of UKF theory.

Here we use the additive form of UKF, and additive process and measurement noises are considered for the nonlinear dynamic system (1)-(3). In [25], it is proved that the nonaugmented Unscented Transformation (UT) is identical to the augmented UT if the condition of $n+\kappa = const$ is satisfied, which is the case here. The only basic difference between the two alternative versions of UKF is that the augmented UKF draws a sigma points set only once within a filtering recursion, while the nonaugmented UKF has to redraw a new set of sigma points to incorporate the effect of additive process noise. Because the computational complexity of nonaugmented UKF is lower, we use this form in our work.

The nonaugmented UKF using the matrix form of UT, for a nonlinear discrete-time system (26)-(27), consists of the following steps, [26].

1) UKF prediction step: Compute the predicted state mean m_k^- and the predicted covariance P_k^- as

$$\begin{aligned} X_{k-1} &= \begin{bmatrix} m_{k-1} & \dots & m_{k-1} \end{bmatrix} \\ &\quad + \sqrt{c}\begin{bmatrix} 0 & \sqrt{P_{k-1}} & -\sqrt{P_{k-1}} \end{bmatrix} \qquad (6) \\ \hat{X}_k &= f(X_{k-1}, k-1) \qquad (7) \\ m_k^- &= \hat{X}_k w_m \qquad (8) \\ P_k^- &= \hat{X}_k W [\hat{X}_k]^T + Q_{k-1} \qquad (9) \end{aligned}$$

where X is the matrix of sigma points, $c = \alpha^2(n+\kappa)$, the parameter α determines the spread of the sigma points around x and usually set to $10^{-4} < \alpha < 1$. For α, the smaller the value, the smaller the sigma-point spread and the less likely to pick up anomalous effects in the distribution, parameter $\kappa \geq 0$ is not critical and is often set to zero [27], n is the dimension of the state equations, Q is the process covariance matrix, and vector w_m and matrix W are defined as follows:

$$\begin{aligned} w_m &= \begin{bmatrix} W_m^{(0)} & \dots & W_m^{(2n)} \end{bmatrix}^T \qquad (10) \\ W &= \left(I - \begin{bmatrix} w_m & \dots & w_m \end{bmatrix}\right) \qquad (11) \\ &\quad \times \operatorname{diag}\left(W_c^{(0)} \quad \dots \quad W_c^{(2n)} \right) \qquad (12) \\ &\quad \times \left(I - \begin{bmatrix} w_m & \dots & w_m \end{bmatrix}\right)^T \qquad (13) \end{aligned}$$

where

$$W_m^{(0)} = \frac{\lambda}{(n+\lambda)} \qquad (14)$$

$$W_c^{(0)} = \frac{\lambda}{(n+\lambda) + (1 - \alpha^2 + \beta)} \qquad (15)$$

$$W_m^{(i)} = \frac{1}{2(n+\lambda)}, \quad i = 1, ..., 2n \qquad (16)$$

$$W_c^{(i)} = \frac{1}{2(n+\lambda)}, \quad i = 1, ..., 2n \qquad (17)$$

are the weights associated with the sigma points in (6), the parameter $\lambda = \alpha^2(n+\kappa) - n$ is a scaling parameter, and the constant β is used to incorporate part of the prior knowledge of the distribution of x and for Gaussian distribution $\beta = 2$ is optimal [23], [28].

2) UKF update step: Compute the predicted mean μ_k and covariance of the measurement S_k, and the cross-covariance of the state and measurement C_k:

$$\begin{aligned} X_k^- &= \begin{bmatrix} m_k^- & \dots & m_k^- \end{bmatrix} \\ &\quad + \sqrt{c}\begin{bmatrix} 0 & \sqrt{P_k^-} & -\sqrt{P_k^-} \end{bmatrix} \qquad (18) \\ Y_k^- &= h(X_k^-, k) \qquad (19) \\ \mu_k &= Y_k^- w_m \qquad (20) \\ S_k &= Y_k^- W [Y_k^-]^T + R_k \qquad (21) \\ C_k &= X_k^- W [Y_k^-]^T \qquad (22) \end{aligned}$$

where R is the measurement covariance matrix. Finally compute the filter gain K_k and the updated state mean m_k and covariance P_k, conditional to the measurement y_k:

$$\begin{aligned} K_k &= C_k S_k^{-1} \qquad (23) \\ m_k &= m_k^- + K_k[y_k - \mu_k] \qquad (24) \\ P_k &= P_k^- - K_k S_k K_k^T \qquad (25) \end{aligned}$$

IV. Joint Unscented Kalman Filter

In this paper we consider the problem of simultaneously estimating both the states and model parameters of a discrete-time nonlinear system from the noisy measurements. A number of approaches have been proposed for this problem, including joint and dual unscented Kalman filter methods [27], [29]. The dual UKF algorithm uses two parallel UKFs to estimate the states and the parameters successively. At every time step, the current estimate of the parameters is used in the state filter, and the current estimate of the state is used in the parallel parameter filter. In the joint UKF, the state and model parameters are concatenated into a combined state vector, and a single UKF is used to estimate both quantities simultaneously. The main difference between the two approaches, in addition to the number of required filters, is that the joint filter explicitly allows for statistical dependence between states and parameters. While on the contrary in the dual filtering approach the cross covariances are not explicitly estimated, so that it effectively assumes independence. It could be argued, therefore, that if correlation is suspected between states and parameters, the joint approach would be preferred [27], [30]. However, experiments performed by [27] show little difference between the two approaches. The reason might be due to implicit dependence introduced by the state-parameter switching at each period using the dual approach.

Here we first discretize continuous-time system using first order Euler approximation to get a discrete-time system in the following form

$$\begin{aligned} x_k &= f(x_{k-1}, k-1) + q_{k-1} \qquad (26) \\ y_k &= h(x_k, k) + r_k \qquad (27) \end{aligned}$$

where $x_k \in \mathbb{R}^n$ is the state, $y_k \in \mathbb{R}^m$ is the measurement, $q_{k-1} \sim N(0, Q_{k-1})$ is the Gaussian process noise, and $r_k \sim N(0, R_k)$ is the Gaussian measurement noise.

Using a joint estimation approach, we represent unknown parameters as part of the state vector and estimate their values using the UKF in conjunction with $x_1 = p_p$, $x_2 = q$ and $x_3 = p_c$. The corresponding dynamic model is written as

$$\begin{bmatrix} x_{1,k} \\ x_{2,k} \\ x_{3,k} \\ \theta_{1,k} \\ \theta_{2,k} \end{bmatrix} = \begin{bmatrix} f_1(x_{k-1}) \\ f_2(x_{k-1}, \theta_{1,(k-1)}) \\ f_3(x_{k-1}, \theta_{2,(k-1)}) \\ \theta_{1,(k-1)} \\ \theta_{2,(k-1)} \end{bmatrix} \tag{28}$$

The time-update for the latter portion of the augmented state vector allows no changes beyond the effects of process noise, i.e. the parameters should be constant. The strength of the noise should correspond roughly to the possible range of parameter variation.

V. Simulations

In this section, we present the simulation results for the joint UKF method. In the following simulations, the parameter values for MPD model and UKF are summarized in Table I. The augmented process covariance matrix used in the joint state-parameter estimation is

$$Q = \text{diag}\begin{bmatrix}10^{-3} & 10^{-9} & 10^{-3} & 10^{-12} & 10^{-12}\end{bmatrix} \tag{29}$$

which is determined based on physical intuition of the system and some trial and error. The pump and choke pressure measurements are corrupted by zero mean additive white noise with the following covariance matrix

$$R = \begin{bmatrix} 0.1 & 0 \\ 0 & 0.1 \end{bmatrix} \tag{30}$$

Furthermore, the steady-state friction characteristic of the well hydraulics, in (3), is modeled according to $F(q) = F_d(q)+F_a(q)$, were the friction in the drillstring and annulus are approximated by the following second-order polynomials [7],

$$F_d(q) = 366.6q + 146570q^2 \tag{31}$$
$$F_a(q) = 304.9q + 5188q^2 \tag{32}$$

where $F_d(q)$ corresponds to the frictional pressure loss from the main pump to the bit, and $F_a(q)$ corresponds to the frictional pressure loss from the bit to the choke.

TABLE I
Parameter Values

Parameter	Value	Parameter	Value
β_d	14000 [bar]	β_a	14000 [bar]
ρ	1210 [kg/m^3]	M	8300 [kg/m^4]
K_c	0.0056	V_a	100 [m^3]
h_{TVD}	1825 [m]	V_d	42 [m^3]
g	9.81 [m/s^2]	q_{bpp}	400 [LPM]
p_0	1.01325 [bar]	T_s	0.01 [s]
α	0.5	β	2
κ	0		

The initial conditions for the states and parameters are as follows

$$\begin{bmatrix} x_1 = 250, & x_2 = 0, & x_3 = 50, & \theta_1 = 2, & \theta_2 = 0.1 \end{bmatrix}$$

In this simulation, first the main pump flow is set to 2000 LPM and choke opening to 100%, then at $t = 300s$ the main pump is shut off to perform connections, and therefore significant pressure drop in the well is apparent. At $t = 480s$ the choke is closed to 13% to compensate for the pressure drop. Next after doing connections, at $t = 800s$ the main pump is set to 1500 LPM and choke opening to 60%. Figures 2 and 3 show measured and estimated pump pressure, and choke pressure respectively. The flow through the bit and downhole pressure are shown in Figures 4 and 5, respectively. Friction factor and bulk modulus parameter estimation results are illustrated in Figures 6 and 7, respectively. Friction factor coefficient estimation has a very fast convergence rate, of about less than five seconds, but for the case of bulk modulus coefficient estimation it takes much longer and it is of the order of minutes. Although after about 10 seconds the estimation error is less than 4 percent.

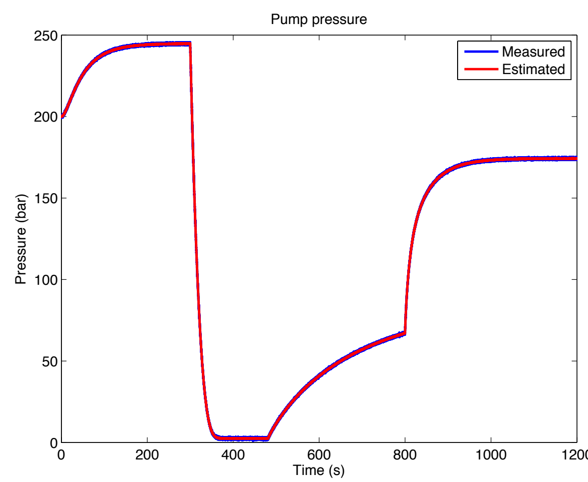

Fig. 2. Measured and estimated pump pressure.

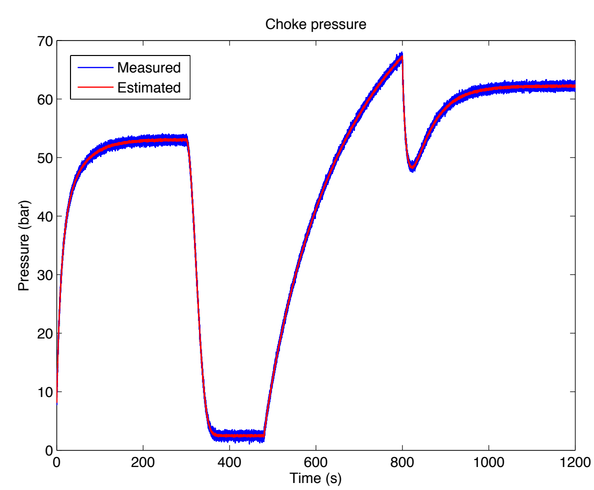

Fig. 3. Measured and estimated choke pressure.

It is important to verify the convergence of a nonlinear estimator from different initial conditions. Friction factor and bulk modulus parameter estimation results for different initial

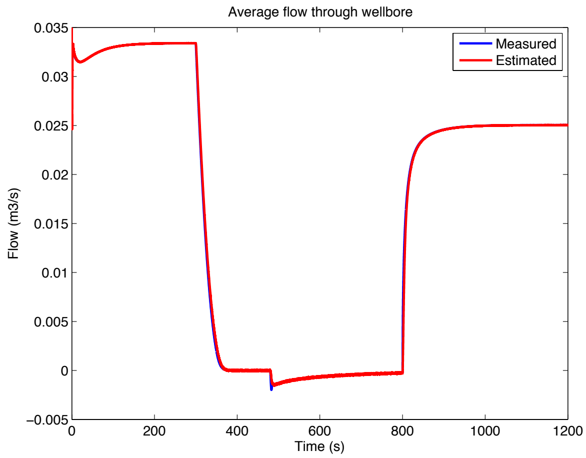

Fig. 4. Real and estimated average flow through the wellbore.

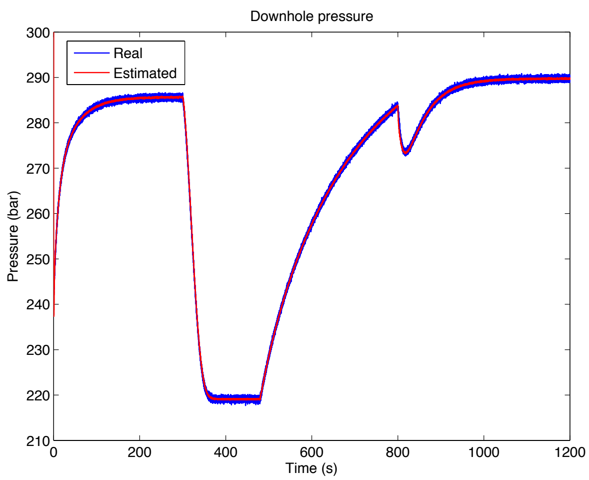

Fig. 5. Real and estimated downhole pressure.

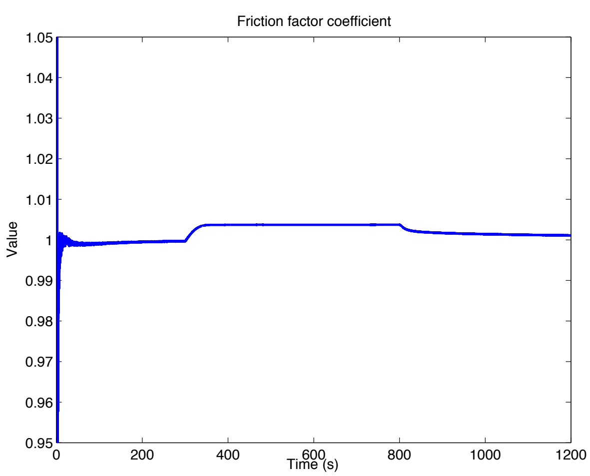

Fig. 6. Friction factor parameter estimation.

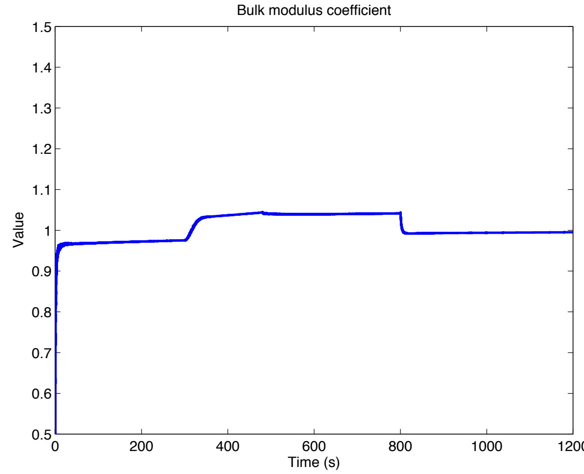

Fig. 7. Bulk modulus parameter estimation.

conditions are shown in Figures 8 and 9, respectively. Clearly for all initial conditions joint UKF converges to the true parameter value. Obviously the closer the initial conditions to the true parameter values, the faster the filter convergence.

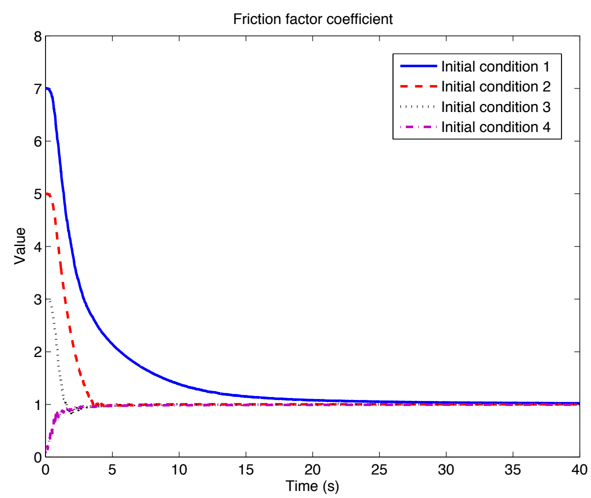

Fig. 8. Friction factor parameter estimation, comparison of different initial conditions.

VI. Conclusions

In this paper, a dynamic model based on mass and momentum balances for managed pressure drilling (MPD) is presented. The sources of uncertainty in drilling operations is discussed and two parameters for calibrating the hydraulic model against uncertainties in the viscosity of mud, temperature distribution in the well, frictional pressure losses, the geometry of the well, and bulk modulus are considered. Frictional pressure losses in the drill-string, annulus, bottom-hole assembly and the bit show nonlinear complex behavior. A joint unscented Kalman filter is designed to simultaneously estimate states and uncertain parameters in the well using only top-side pump and choke pressure measurements.

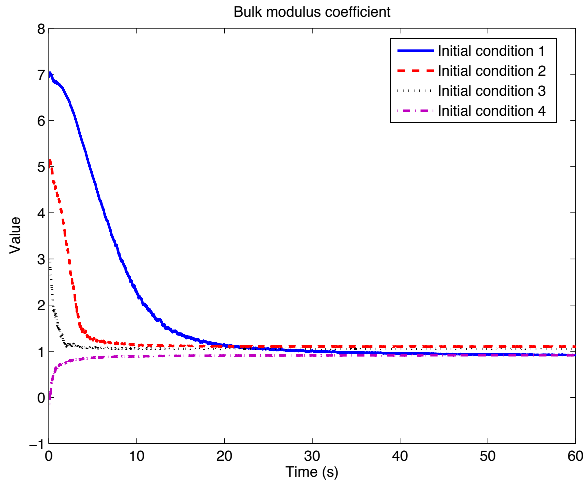

Fig. 9. Bulk modulus parameter estimation, comparison of different initial conditions.

Finally, simulation results are given which show satisfactory performance of joint UKF for state and parameter estimation during both transient and steady-state drilling operations.

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