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A semi-implicit approach for fast parameter estimation by means of the extended Kalman filter

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ABSTRACT

An assessment is performed of the impact of the time-integration scheme on data assimilation based on the extended Kalman filter approach. The usage of the implicit Euler scheme, which leads to unconditionally stable model updates for the whole range of time steps, results in a less accurate estimation of model parameters, which can be overcome using a parameter estimator based on the explicit Euler scheme. However, the latter limits the maximum time step which may lead to an unacceptable increase in computational load. The alternative can be found using a semi-implicit estimator, where a model is updated using the implicit Euler scheme, whereas the propagation of the error covariance matrix in time is based on the explicit time integration scheme. The improved properties of the proposed algorithm are demonstrated on a one-dimensional problem of permeability estimation in a porous medium for a single phase oil flow.

1. Introduction

Complex large scale industrial processes can often be described by sets of non-linear partial differential equations. Such equations, which are also known as first principle models, represent conservation of mass, momentum and energy within the system. Supplemented with appropriate boundary and initial conditions these describe the performance of the system in a continuous form. Such rigorous models can very accurately predict process behaviour, provided that the correct closure equations are available.

There are many industrial processes where the model parameters should be adjusted as these parameters are poorly known [1,2]. In particular, reservoir engineering requires the knowledge of the properties of a porous medium. In this case the values of permeability and porosity of the medium determine the pressure and velocity distribution in the reservoir and, consequently, the accuracy of the prediction of the oilfield performance [3,4]. However, due to high costs related to a direct measurement of the reservoir properties, combined with significant geological heterogeneity, there is an uncertainty in reservoir characterization. This, in turn, may result in poor performance of forward reservoir simulators and corresponding decrease of oil production.

This problem can be overcome by using data assimilation techniques (which are also referred to as history-matching or soft-sensing in petroleum engineering nomenclature) [5]. In this approach, the poorly known unmeasured parameters are estimated by means of combining all the available observations with a dynamic model of the system. Contrary to the forward problem, which consists of computing the distribution of pressures/velocities in the oilfield, the inverse problem consists of determining the unknown parameters from known (measured) dynamic variables. These measurements are usually quite sparse for hydrocarbon production systems, as the number of locations for sensors is very limited and available only in wells. The best estimate of the reservoir properties is calculated by minimizing the mismatch between the model prediction and measurements. Here one can note two different approaches. Variational data assimilation, which is based on the minimization of a cost function within a certain time interval [6] and sequential history matching methods or filtering, where the state of the system is updated every time instant new data become available. The latter updates reservoir properties in real-time, as new measurements are introduced in the assimilation process. For these purposes the sequential algorithms continuously update an initial estimate based on ongoing experimental measurements.

One way to solve these sequential data assimilation problems is to use Kalman filtering [7], which was originally developed for linear models. The Kalman filter is the optimal state estimator in least square sense for linear models with both model and measurement error described by a Gaussian distribution. This algorithm has a predictor–corrector structure with first the state variables calcu-

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