Injection Scheduling Design For Reduced Order Waterflood Modeling

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Motivation & Introduction

In this work we are going to address the idea of designing a proper experiment for the purpose of approximating the two phase waterflooding process with a low order data driven model. In sum, reduced order modeling performance can be improved by providing a more informative data. A prior knowledge about the dynamics of the process can help to design and adapt an injection schedule to provide such data. Since the model structure is linear, it is of the most importance that the schedule keeps the process in its linear regime while exciting the relevant dynamics. Therefore, designing a proper injection schedule boils down to understanding the production constraints that limit the design parameters and reaching to an optimal trade-off, to have as informative of a data as possible. The novelty of this work is that we look into this problem from reservoir engineering angle as well as the requirements from system identification viewpoint.
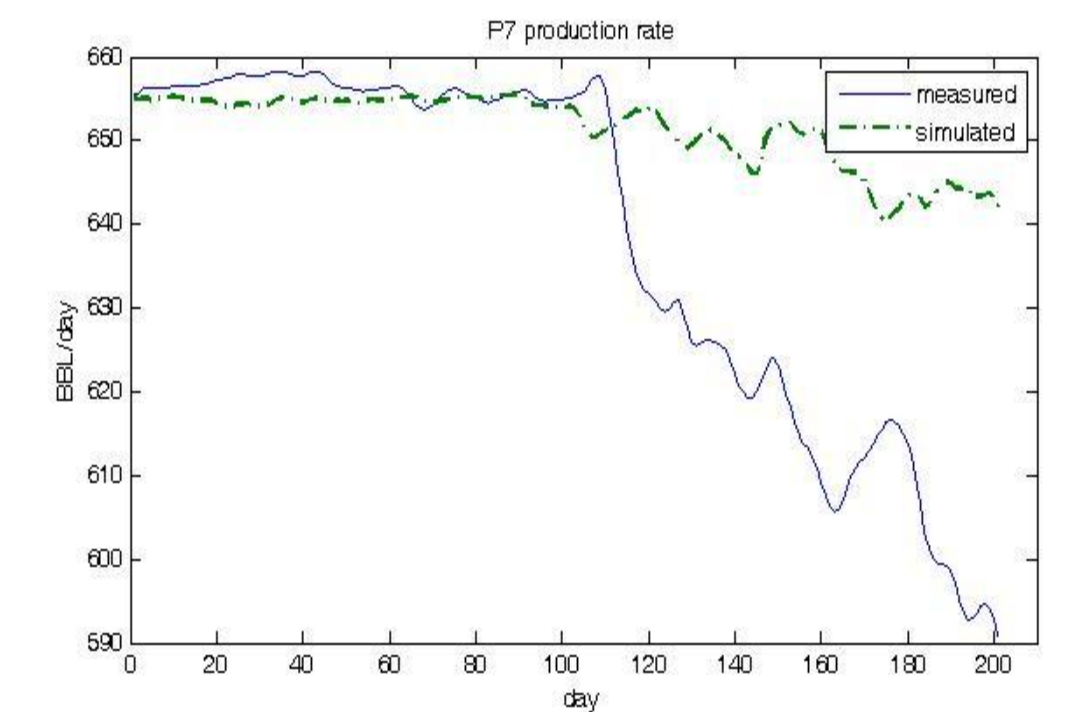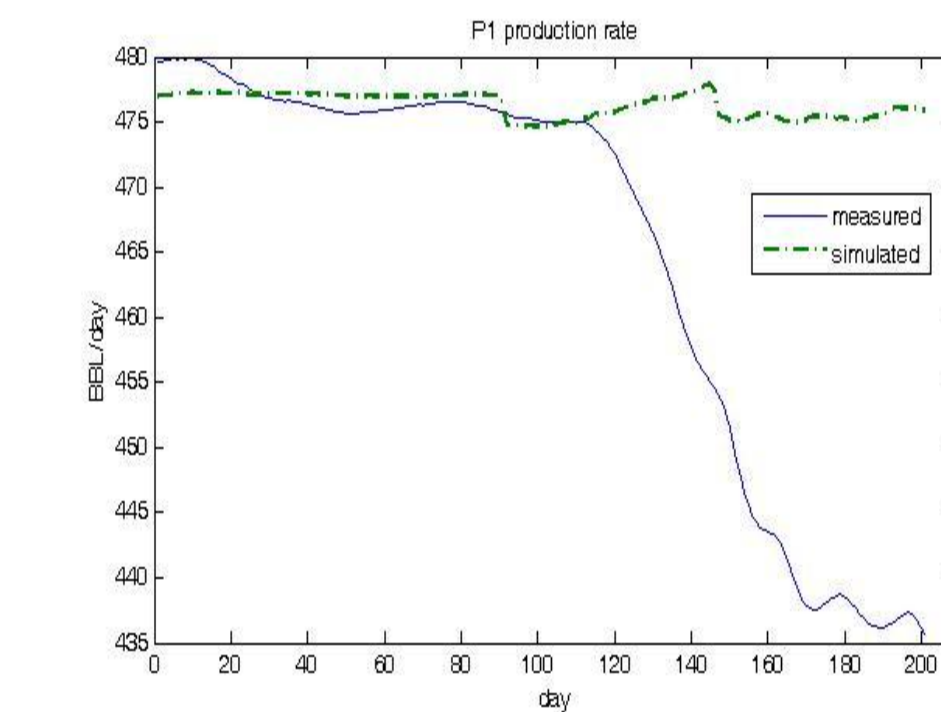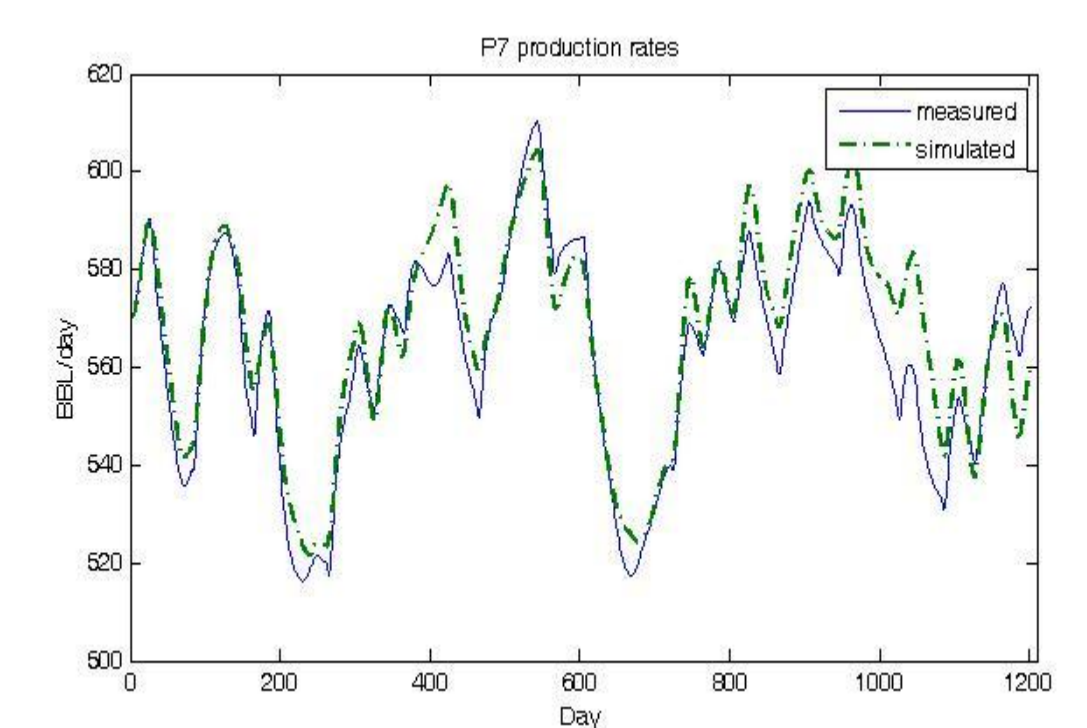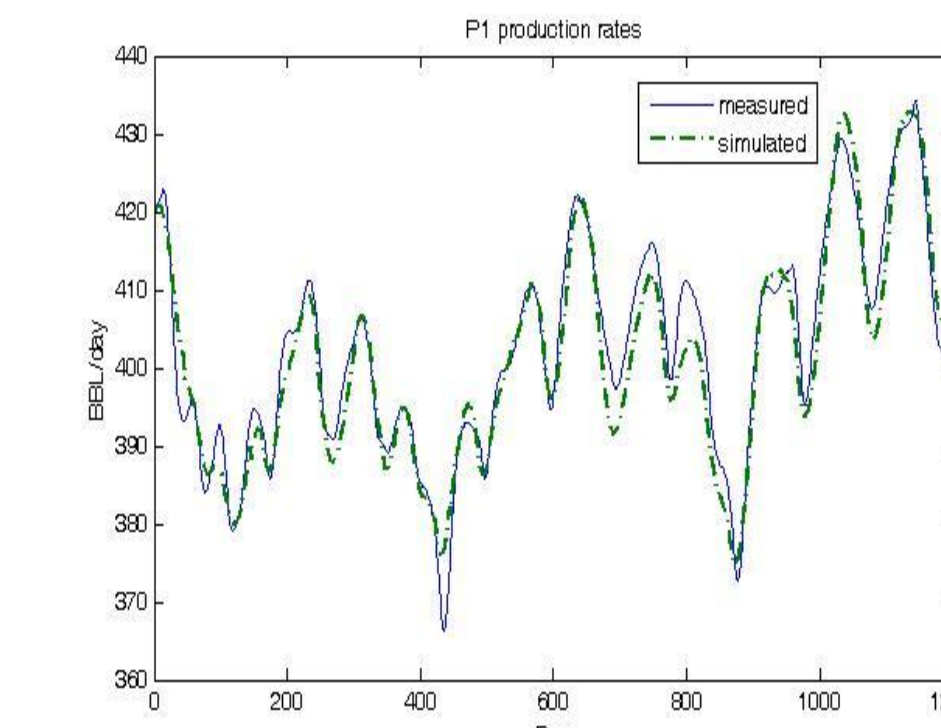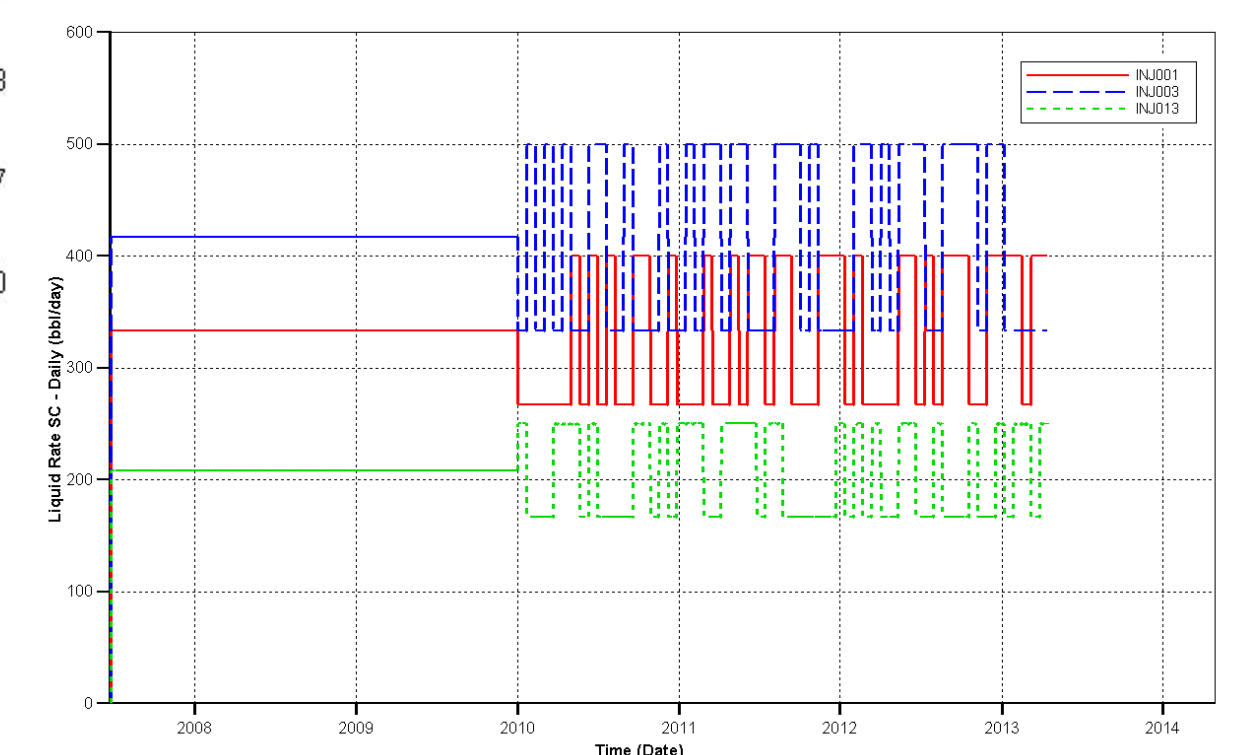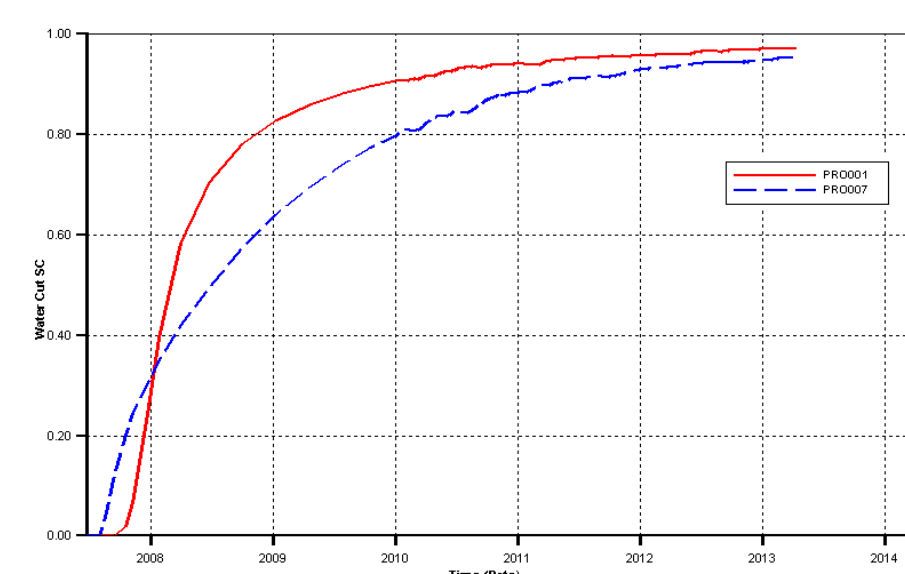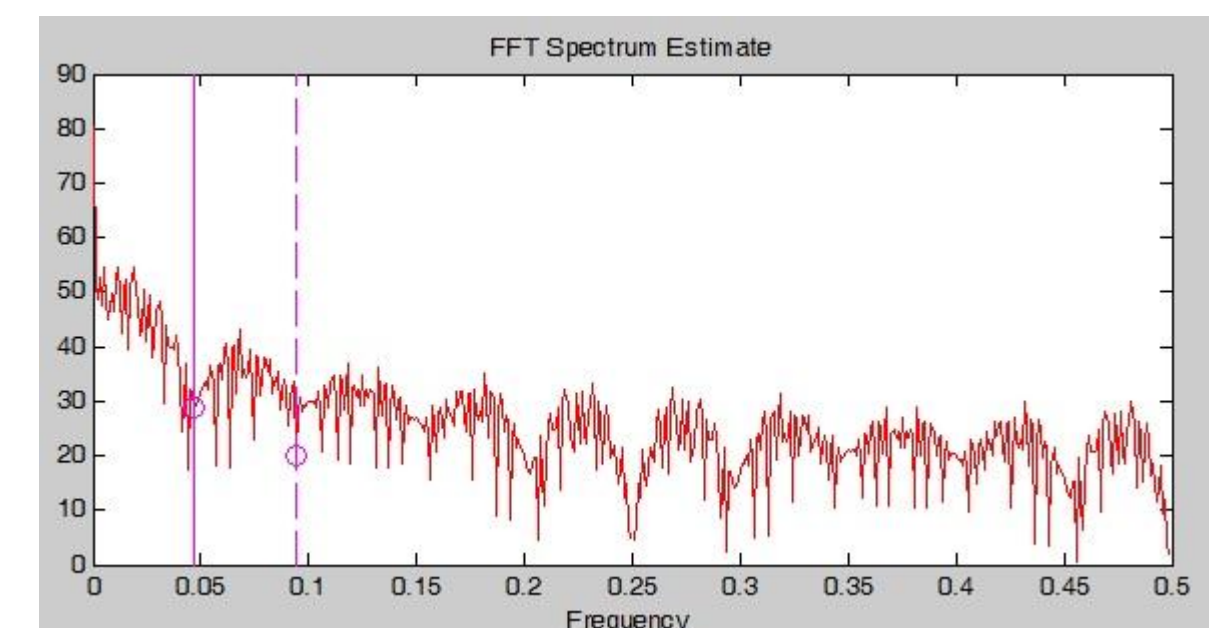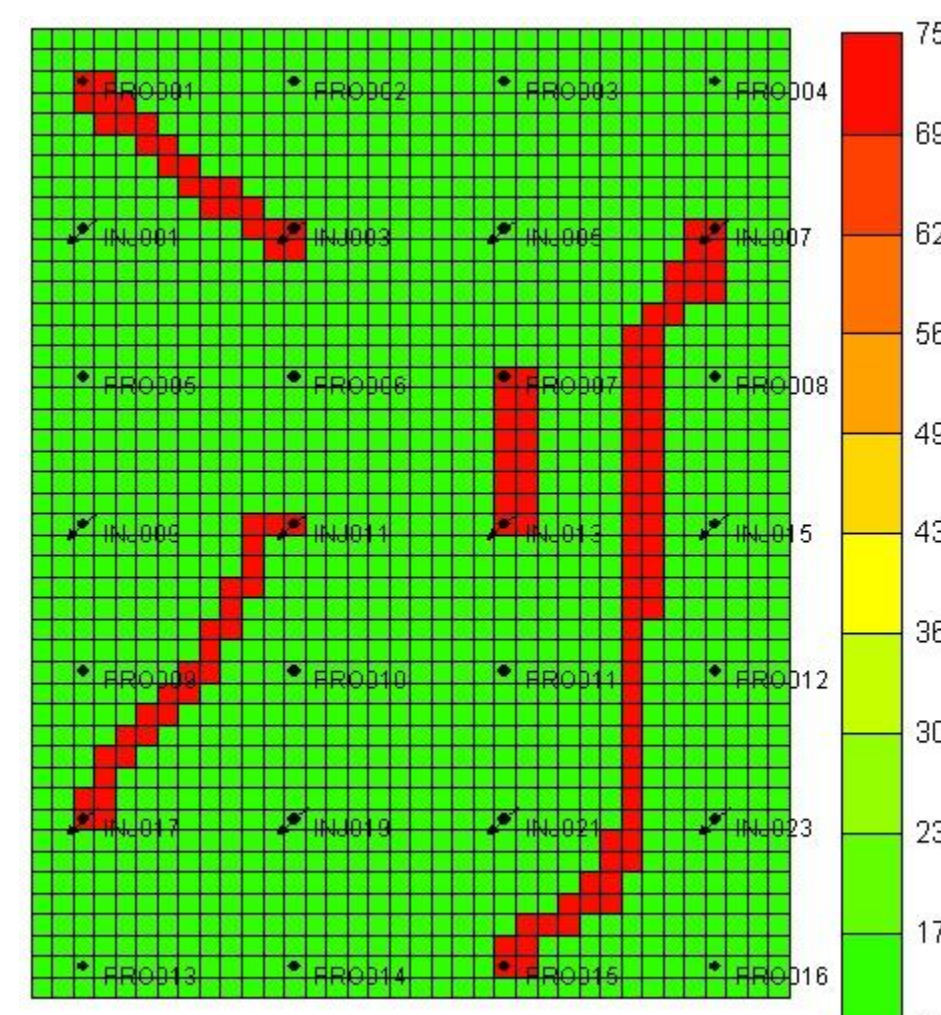
Experiments

A proper injection scheduling is an iterative design process, i.e. based on the information we acquire from the system during model training and validation, the design parameters should be modified to meet the modeling needs. To show the benefits of scheduling design, we present a simple procedure on a reservoir model developed in CMG simulator.

Applying the input/output measured data, a 4th order ARX model is identified from injectors J1 and J3 to producer P1, and similarly from injectors J3, J5, J7, J11, J13 and J15 to producer P7. The simulated production rates for the first 1000 days and the prediction of the rates for the following 200 days are shown in Figure IV and IV for P1 and P7 respectively. The Root Mean Squared Error (RMSE) of the prediction is $3.5 BBL/day$ and $14.6 BBL/day$ for P1 and P7.

Another set of injection schedule is designed. The training period of this schedule is short 100 days and the rates are changing rapidly. Moreover, the amplitude of injection rates are not so high and it only varies 5% of the nominal injection rates. After 100 days, another set of 100 days is applied to evaluate the prediction quality of the identified models. It can be seen that although the simulated production rates are close to the measured rates (which might be very trivial), the predictions are very off. RMSE of prediction period is $19.1 BBL/day$ and $22.3 BBL/day$ for P1 and P7. This experiment also verifies that in order to have a meaningful prediction, the experiment for the training phase must excite the similar dynamics of the prediction phase.

Data

P1 production rates

P7 production rates

P1 production rate

P7 production rate

Discussion & Future Work

There is a number of design parameters that needs to be determined according to the dynamics of the system such as length of experiment, frequency of changes in the input, amplitude of injection rates and etc. The proposed methodology here consists of designing a set of mutually uncorrelated PRBS sequences for injection rates. The amplitude of the injection rates are varying above and below the nominal injection rate, such that overall injected water remains the same. In this way, unnecessary production decline can be avoided while the pressure and saturation pattern of the field can almost stay as if no scheduling is applied. It is very important that the saturation does not vary too much, since it is the main source of nonlinearity in the system. Therefore, the length of the experiment is constrained by this factor, and usually a mature field can satisfy a long training period. The frequency of the variations should be fast enough to cover 2 or 3 times of the system's frequency band of interest. Waterflooding is naturally a slow process and thus it does not need a fast changing input. The fastest well-test response from an injector to producer can be a good indicator of how frequent the injection rates must change. Results in the last section show that a well designed input signal can significantly improve the training of the reduced order linear model parameters. Here we used 4th order ARX model between a single producer and its neighbor injectors. It should be noted that the system identification and schedule design is an iterative task. For example, although in the above experiment a period of 1000 days is chosen for training and 200 days for prediction, it does not necessarily mean that one should wait until 1000 days before so identified model is useful for 200 days. Instead a *moving window* of training and validation can be defined, and more measurements are fed back to the analysis, and therefore improve the prediction results. This work can be further extended by specifically looking into model identification for a certain structure. In fact the modeling and schedule design must be integrated for better results.

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