

Introduction

Carbon Capture and Storage technology (CCS) stands for the collection of CO_2 from industrial sources and its injection underground. Carbon dioxide is stored in a deep geological formation that is sealed on a top by a low permeability cap [1]. Subsurface storage of CO_2 is always associated with an excess pressure in the reservoir and one of the primary environmental risks is a pressure-driven leakage of CO_2 from the storage formation. [2, 4].

The problem of an injection well placement is an important issue that can contribute significantly to the risk mitigation. In order to assess the risk of CO_2 leakage through the caprock we can simulate different potential well placement scenarios and subsequently we can place the injector giving the minimum risk. However, it can be infeasible in case of complex simulation models and numerous possible placements for the reason of an excessive simulation time. At the same time response surface modeling is intended to approximate complex and computationally demanding simulator codes with lower time costs basing on a limited number of simulations. In this work we focus on Gaussian Process (GP) model and we propose to approximate the reservoir simulator output with its response surface model by taking well positions and a time step as controllable discrete paramaters. So that, instead of looking over all the possible combinations of the well positions during the simulation period we run a unique model for the analysis. The suggested approach leads to considerable time-savings and reduction of the number of required simulations.

Methodology

For the problem of well placement the output of the simulator can be represented by $F(\bar{x}, \bar{y}, t)$, where the set \bar{x} represents collectively the uncertain parameters describing the reservoir: porosity, permeability etc. The set of parameters \bar{y} are man-controlled discrete parameters (the well position in our case) and tcorresponds to time step. The objective is to place a well with a minimized risk of leakage. Therefore, the objective function to approximate by a response surface model is the reservoir overpressure increase in the upper layer of the reservoir. As soon as the response surface model is genereated and validated, to be more confident about the risk we aime to estimate P90 of $F_{\bar{x}}(\bar{y})$ as function of controllable parameters \bar{y} at every time step basing on Monte-Carlo sampling the set of uncertain parameters \bar{x} . After that, the optimal well position \bar{y}^* is a solution of the following optimization problem:

$$\bar{y}^* = argMin(F_{\bar{x}}(\bar{y})).$$

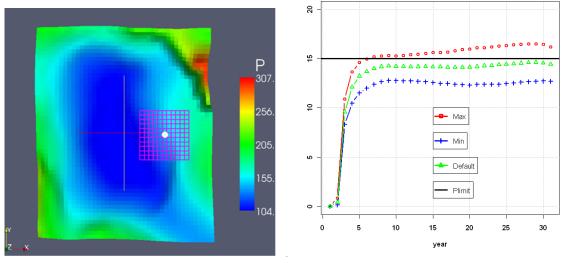
Application

The method was tested on a reservoir model of potential CO_2 storage site in Denmark. The reservoir simulation model was constructed from incomplete or lacking data, and can include significant uncertainties. Initial storage pressure is assumed to be at the hydrostatic conditions. The CO_2 injection is supposed to be at a constant rate for the period of 30 years. Following the engineering safety reasons, the margin on the cap rock will allow a pressure increase of about 15 % compared to static condition. Therefore, the maximum allowed overpressure is $P_{limit} = 15$ bars. Exceeding this value can lead to a leakage. The injection well is to be placed inside the predetermined region that is represented in Figure 1(a) with the original pressure distribution map. Each coordinate includes 11 possible levels.

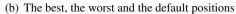
The uncertain parameters \bar{x} selected for this study characterize the reservoir and the fluid properties and imply different CO_2 flowing possibilities between the reservoir layers. The well position cell number refers to the controllable parameters to be optimized.

The first step is an approximation of the overpressure in the upper layer by a response surface model and the model validation. After that, if the satisfactory predictivity is achieved, by fixing controllable parameters of well positions and Monte-Carlo sampling the uncertain parameters, we can go over all the possible 121 coordinates combinations and estimate P90 of the realizations. Afterward, the optimum well position that provides the minimum overpressure estimation can be identified.





(a) Original reservoir pressure distribution



P90 overpressure over the years

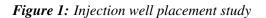


Figure 1(b) represents the possible overpressure evolutions and compares the overpressure development over simulation period for the best, the worst and the default well postion that was used in the original simulation model. The optimal well position corresponds to [X,Y] = [36,32]. Whereas, placing an injection well in [X,Y] = [26,32] can lead to a leakage.

Conclusions

In this work we propose a new method for a well placement optimization under uncertainty, particularly CO_2 injector placement. The method is based on approximation the reservoir overpressure by GP response surface model where we consider the well position as a controllable discrete variable. We applied the method to a real potential CO_2 reservoir case. The injection well position is determined under minimization of the possible leakage risk. The case demonstrated a reliable level of predictivity. Moreover, including controllable parameters in the GP modeling allows to considerably reduce the required number of simulations. Therefore the method provides significant time savings compared to the standard approach.

References

- [1] Busch, A., Amann, A., Bertier, P., Waschbusch, M., Kroos, B.M. (2010). The Significance of Caprock Sealing Integrity for *CO*₂ Storage. SPE.
- [2] Bowden, A.R., Rigg, A. (2004). Assessing risk in CO₂ storage projects. The APPEA Journal. Vol.:677-702.
- [3] Santner, T.J., Williams, B.J., Notz, W.I. (2003). The Design and Analysis of Computer Experimens. Springer Series in Statistics.
- [4] S.M. Benson. (2006). Assessment of Risks from Storage of Carbon Dioxide in Deep Underground Geological Formations. Earth Sciences Division of Lawrence Berkeley National Laboratory.
- [5] Sacks, J., Welch, W.J., Mitchell, T.J., Wynn, H. (1989). The Design and Analysis of Computer Experiments. Statistical Science, Vol.:409-435.
- [6] Busby, D. (2009) Hierarchical adaptive experimental design for Gaussian process emulators. Reliability Engineering and System Safety. 94, 1183-1193.