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Evaluation of rapid performance reservoir models for quantitative risk assessment

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Abstract

The National Risk Assessment Partnership (NRAP) is a research organization focused on developing methods and tools for long-term quantitative risk assessment for carbon storage. NRAP’s approach is to divide the carbon storage system into components—reservoir, wells, seals, groundwater, atmosphere—and to develop reduced order models for each of these components. These rapid performance models are trained and/or validated against full physics reservoir models (e.g., TOUGH2, GEM) so that they reproduce similar results but in a fraction of the time of the reservoir model. The different component models can then be combined in an integrated assessment model that can simulate the full system in a matter of seconds or minutes rather than the days, weeks, or longer that a full physics simulation of the entire system would take. The integrated model can then be run in a Monte Carlo mode to assess the probability of failure of a carbon storage system.

In NRAP, part of the focus is on long-term leakage risk, and the rapid performance reservoir models are designed to generate pressures and saturations within the reservoir, and particularly at the reservoir-seal interface, both during injection and for up to 1,000 years post injection. These pressures and saturations can then be used as inputs to wellbore or seal leakage models to predict rates and volumes of leakage of CO2 and/or in situ fluids.

In the past few years, NRAP researchers have developed and applied a number of different reduced order models to saline-, gas-, and oil-bearing storage fields. These models vary significantly in several respects. They range from lookup tables or response surfaces to models such as polynomial chaos expansion to models that rely on data mining and artificial intelligence techniques. Each of these types of rapid performance models has different strengths and weaknesses, depending on the method used, the reservoir type, and the goals.

In all cases, the rapid performance models required a geologic model and at least some traditional reservoir simulation runs for training or validation purposes. Also, in all techniques developed, an initial analysis is performed to reduce the number of input parameters and scenarios needed for the final simulations. The number of reservoir simulation runs needed can vary significantly based on the reduced order model used. The time and sophistication that it takes to develop a reduced order model is another major factor that varies among the different types of models. Some models are easily able to handle a significant number of varying spatial inputs, while others are limited in the number of input parameters available. Additionally, while all of the rapid performance models will run much faster than a reservoir model, there run times can vary from fractions of a second to tens of seconds or longer, depending on the situation being modeled.

This paper will describe the different types of reduced order reservoir models used within NRAP. It will also provide a critical assessment

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of these rapid performance models, discuss under what circumstances different rapid performance models would be most effective, and evaluate their utility in the context of quantitative risk assessment.

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1. Introduction

The National Risk Assessment Partnership (NRAP) is a multi-national lab research collaboration between the National Energy Technology Lab (NETL), Lawrence Berkeley National Lab (LBNL), Lawrence Livermore National Lab (LLNL), Los Alamos National Lab (LANL), and Pacific Northwest National Lab (PNNL). NRAP is developing methods and tools for long-term quantitative risk assessment for carbon storage. The approach being taken is to develop an integrated assessment model that can be run in a Monte Carlo fashion to assess the probability of failure of a carbon storage system and the associated uncertainty. The first step is to divide the carbon storage system into components—reservoir, wells, seals, groundwater, atmosphere—each of which can be simulated separately by a reservoir simulator or similar model. Unfortunately, these component models are often not fast enough that a Monte Carlo simulation (with thousands to tens of thousands of realizations) can be performed with them in a reasonable amount of time (e.g., hours to days). To address this issue, NRAP has developed reduced order models (ROMs) for each component of the carbon storage system. These rapid performance models are trained and/or validated against full physics models (e.g., TOUGH2, GEM) so that they reproduce similar results but in a fraction of the time that it takes to run the more detailed models.

This work focuses on the evaluation of reduced order models for the reservoir component of the carbon storage system. Four distinct reservoir ROMs were built for three different storage site types—saline formation, gas field, oil field—using three different approaches. The ROMs were designed to predict the pressures and saturations within the reservoir at the reservoir-seal interface as a function of time, both during injection and post injection. The top of the reservoir was chosen because the goal of the ROM development was to fit within an integrated assessment model that focuses on leakage risks, and the pressures and saturations at the reservoir-seal interface are used as inputs to well or seal leakage models.

2. Reservoir Models

2.1. Saline aquifer

By far, the largest amount of carbon storage capacity in the US (and the world) can be found in saline formations [1]. The saline aquifer studied here is based on a site in the Southern San Joaquin Basin in California, USA. It is a sandstone formation with a moderately complex geometry and a number of faults generally considered to be sealing. The reservoir was modeled for the site was developed using TOUGH2-MP [2], a massively parallel version of the TOUGH2 software. The site modeled was approximately 6 km² in size, and 5Mt of CO2 was injected per year for 50 years with >200 years of post-injection time. A sensitivity study was performed to identify the variables with the greatest contributions to reservoir pressures and saturations, and the three variables that had the highest impact were reservoir porosity, reservoir permeability, and seal permeability. A heterogeneous porosity and permeability distribution were generated for the reservoir, and set as a function of depth. Seal permeability was varied homogeneously by a few orders of magnitude in different realizations. A detailed description of the model and the runs used in the sensitivity study can be found elsewhere [3].

2.2. Gas field

Although not as great a potential capacity for storage as saline formations, gas fields make up a substantial volume of potential storage with proven seals. The gas field studied here is based on an actual pilot CO2 storage site in southern Australia near Melbourne. The site is associated with phase I of the Otway project, and much detail on the site can be found elsewhere [4]. The reservoir was a primarily sandstone reservoir with a very complex geometry and a substantial fault that partially divided the reservoir. A heterogeneous porosity and permeability field were used in the reservoir simulations, as generated through a history-matching process based on the pilot CO2 injection at the site. Simulations were performed using CMG’s GEM-GHG software for ~1-4 years of injection at rates between 35-100kt/yr with 200 years of post-injection simulation. The site modeled was approximately 2 km² in size. Detailed information about these simulations can be found elsewhere [5].
2.3. Oil field

Oil fields have potential for early action in terms of carbon dioxide storage because of the opportunity to generate revenue through the enhanced oil recovery (EOR) process. The oil field studied here is based on the SACROC field in west Texas, which has undergone decades of CO2-enhanced oil recovery and which is a part of the Southwest Regional Partnership for carbon storage [6, 7]. The reservoir is a reef carbonate with moderate heterogeneity, and the portion simulated is part of a domal structure (see Figure 1) about 10 km² in size. Simulations were performed using TOUGH2 and an upscaled porosity and permeability distribution based on a history-matched model [6]. In this model, 22 production wells throughout the field were simulated through a hypothetical end of production based on oil recovery rates, and then all 22 wells were converted to injectors and were simulated injecting at constant (but varying by realization) pressures for 50 years, with a >200 year post injection simulation time. Detailed information about these simulations can be found elsewhere [8].

![Figure 1. Oil field SACROC reservoir permeability field](image)

3. Reduced order modelling approaches

In all of the reduced order modeling approaches described below, the detailed reservoir simulator was considered to be an accurate source of behavior of the system. Results from the reservoir simulation were used to train the ROMs, and an evaluation of their accuracy was based on a comparison between the ROM results and the reservoir simulator results. The approach for ROM validation was to hold a percentage of reservoir simulation runs (~10%) out of the training data set and using them to make direct comparisons on a grid block by grid block basis between the ROM and the full-physics model (e.g., TOUGH2).

3.1. Lookup Table

The lookup table (LUT) approach is a very simple method of ROM development, but it relies on many detailed reservoir simulations to give enough parameter resolution. Essentially, the generation of a LUT consists of running tens to hundreds of simulations for multiple input parameters of importance (identified, for instance, through a sensitivity study). Then, a table of input parameter X₁, ..., Xₖ and output parameter profiles W₁(t), ..., Wₖ(t) are created. The time dependence of the parameters could be accounted for in a couple of ways: 1) by fitting a characteristic polynomial or non-parametric function to the time-dependent output for each variable or 2) by discretizing the time-dependence and generating a third dimension for the table that accounts for time. This table can then be used to identify the values of the output parameters for any realization at any location or time based on interpolating between the appropriate entries.
A LUT approach was used for the saline formation site described above. The table of input parameters was developed based on a sensitivity study using over 300 simulations with TOUGH2; reservoir permeability, reservoir porosity, and seal permeability were the values identified. The two output variables used were the pressure and saturation at each (x,y) grid location of a 100 x 100 grid at the reservoir-seal interface. The second approach for time-dependence was used in this study in part because it was not easy to find a simple curve to fit to the time-dependent profiles. For the injection phase, time steps of every five years or so were used, but those became longer and up to 200 years in the post injection period (for 1000 year simulations). The results from these >300 simulations were combined into a table, and a scanning routine was used to appropriately interpolate between the table entries so that reservoir-seal interface pressures and saturations could be generated quickly based on input parameter values. The result is a very fast ROM that generally gives outputs for a single realization (through all time steps) in less than a second.

The accuracy of the ROM was also tested to be within 10% of the value of the reservoir simulator in more than 95% of the cases, with the only discrepancies being where large time discretizations were used. Also, the number of simulations needed for the LUT generation was able to be reduced by approximately a factor of 5 by using the code PSUADE [9] and a Latin Hypercube Sampling technique. More detail on the simulations behind the LUT development can be found elsewhere [10].

3.2. Artificial intelligence and data mining approach

The artificial intelligence and data mining approach was taken for the gas and oil field reservoirs, in the form of what is termed a Surrogate Reservoir Model (SRM). The SRM approach is much more complicated than the LUT, but it is more flexible and requires many fewer reservoir simulation runs to train the ROM. The approach used in this study is a grid-based approach and essentially uses fuzzy logic and reservoir simulation results to train neural networks to predict pressures and saturations across the reservoir-seal interface within each grid block. The following steps are utilized:

- Generate a few initial simulations with full CMG reservoir model (18 simulations)
- Create database of CMG inputs and outputs for each simulation
- Select and organize data to ensure appropriate relationships between less or more distant neighbor cells are captured; generate SRM input
- Train neural networks (here using 2% of the CMG input/output tables), calibrate, and verify for each parameter of interest
- Apply neural networks to blind scenarios for testing

Detailed descriptions of this technique can be found elsewhere [11, 12].

One of the strengths of this technique is that an SRM is trained so that it predicts reservoir behaviour for heterogeneous porosity and permeability fields. This is different from the LUT, where permeability must be varied through a scalar multiplier. For the SRM, true heterogeneous realizations can be generated with geostatistical software and the SRM is able to predict the behaviour of those reservoirs. This capability is useful if these are data that shows that the reservoir permeability field is behaving spatially differently than the initial estimate. Another strength of this type of ROM is its ability to handle varying injection rates. In short, while the LUT is limited to a relatively small number of independent input variables, the SRM can handle more and spatially variable ones, if it has been trained properly.

An SRM approach was used for the gas and oil fields described above [11, 12]. As for the LUT, there is a need for discretization on the time axis for an SRM approach. Essentially, the SRM is trained for a number of different time steps, and when a pressure or saturation field needs to be known for a time step not trained explicitly, interpolation is used between time steps. The result is a fast ROM that reduces reservoir simulation time from hours or days to 0.5 – 2 minutes, depending on the scenario. The accuracy was also tested to be within 10% of the reservoir simulation value to pressure for >95% of the cases and within 10% of the saturation value for greater than 90% of the grids. The discrepancies in the saturation comparisons generally came right at the gas-brine interface when there were rapidly moving fronts.
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3.3. Polynomial Chaos Expansion

The final ROM development technique that was developed for the reservoirs was the Polynomial Chaos Expansion (PCE) technique that uses mixed-integer programming to make the process more efficient. The PCE technique basically uses a polynomial function of order N to predict outputs on the basis of input values. Again, reservoir simulation outputs are used to “train” the PCE model, or to get the best fit coefficients for the Nth-order polynomial that needs to be fit. Once these coefficients are generated, the resulting polynomial is used to generate pressures and saturations at the reservoir-seal interface for a particular point in time. Figure 2 shows a schematic of how this process works. A detailed description of the PCE technique used for reservoir performance can be found elsewhere [13].

The PCE technique was applied to the oil field model described above. As for the LUT and SRM, the PCE technique again discretized the time and interpolates in between time steps to predict temporal behavior. The PCE model was fast, on the order of a few seconds to run a single realization. The PCE model was able to handle permeability heterogeneity in the case of pressure predictions, but was not demonstrated to perform within 90% accuracy for saturation predictions. Based on earlier work [13], though, the predictions are likely to be much better for an homogeneous or scalar heterogeneous permeability reservoir scenario, such as used for the saline formation. For the SACROC PCE model, >95% of the cases were within 10% of the TOUGH2 simulations for pressure for the training data set and for homogeneous models, but for other heterogeneous permeability values, it has difficult predicting both pressures and saturations.

3.4. Other ROM techniques

The ROMs described above are not an exhaustive list of potential reservoir ROMs, though most potential ROMs are similar to one of the three in a number of respects. Some other potential ROMS include Polynomial Regression, Radial Basis functions [14], or Response Surface techniques. The two former are similar to the PCE technique, and the response surface is similar to the LUT, except that it is more closed form solution than a table that is used. One type of ROM that is different than the ones that have been discussed here is a reduced-physics type of ROM. A good example of this would be the semi-analytical models of Nordbottom and Celia [14].
4. Discussion

Each of the approaches taken to building reservoir ROMs studied here are quite different and they each have positive and negative attributes that make them suitable to different stages in the carbon storage field development process. The different techniques can be compared on the basis of several different factors, and the one discussed here are: 1) ROM complexity, 2) reservoir simulation run time, 3) ROM development time, 4) run time, 5) ROM flexibility, and 6) accuracy of results.

For the LUT technique, the ROM is fairly simple, and anyone who has had experience interpolating between data points can generally understand how this technique works. In the same vein, once the reservoir simulation results are complete, it is a pretty quick task (days) to generate a LUT and to compare results between the LUT and the reservoir model. Also, based on our study, the LUTs developed for pressure and saturation run very quickly (<1s). Most of the time associated with a LUT is in generating the reservoir simulator runs needed to populate the table. It can take 3-6 months to generate the more than 300 runs that were used in this study, unless parallel processing is used. The LHS sampling technique was able to reduce that number by a factor of nearly 5, so that could reduce the lead time to only 1-2 months. This timing, of course, depends on the simulators, the details of the model gridding and parameters, and the hardware that is being used. In terms of flexibility, the LUT is probably the least flexible model in terms of being able to address heterogeneous permeability realizations, which is a major source of uncertainty. On the other hand, for most greenfield sites, there may not be enough data to justify going from a homogeneous to a highly heterogeneous field. Finally, the LUT developed here was able to produce results to the desired accuracy of 90% in most cases, and could be made more accurate by reducing the temporal discretization, at a slight loss of run time speed.

For the SRM technique, the ROM is quite complex, and in general special software will be needed to develop it, such as the neural network add-on to Matlab software. It is also more complicated to incorporate a ROM that requires a heterogeneous permeability distribution as in input parameter into an integrated assessment model. In this case, the number of simulation runs is on the order of 5-20, and so these can be generated relatively quickly (days to weeks). It can take significantly longer to train the neural network to produce the results, probably on the order of 6-12 months for someone not very familiar with the process and shorter (~3 months) for someone with lots of experience. The run time is on the order of 30 seconds to a couple of minutes, so it is much faster than a reservoir simulator, but still takes significantly more time than the 1s of the LUT. The development team believes that that run time can be decreased, and indeed it is about 5 times faster for the SACROC SRM than the Otway SRM (which was developed first). In terms of accuracy of results, the SRMs produced here were able to do a good job at reproducing the results, giving very low error rates for pressures and being within 90% accuracy more than 80% of the time for the saturation predictions. However, the true strength of the SRM is in its flexibility, particularly in how it can handle spatial heterogeneity within the reservoir through multiple realizations. If additional data appropriate for history matching were collected at a carbon storage site, the SRM would be able to rapidly generate simulations to change the uncertainty analysis without any further model development, while for the other ROM techniques, additional simulation runs would be needed to train the updated ROM.
Finally, for the PCE technique, the ROM is not terribly complex, as it involves using regression to fit the coefficients of a polynomial, but incorporating a mixed integer technique to improve efficiency does add some complexity. As for the SRM, the number of simulation runs for the PCE technique needed is fairly small, on the order of 10 for the case studied here. Without the mixed-integer programming, it can take weeks to months to train a PCE ROM, but with the PCE ROM, that time was dropped to days to weeks for the case studied here. The run time is quite fast (a few seconds), if not quite as fast as the LUTs. The PCE ROM is of an intermediate flexibility to the LUT and SRM ROMs. There were some issues with accuracy of the PCE technique for heterogeneous permeability values that were different that what it was trained for. It was better able to predict saturation results (within 90% accuracy) for a homogeneous field, but it can only handle 5-10 different independent variables before the combinations become too complex and efficiency is lost. It also has a difficult time predicting saturation values.

References


