Multi-Objective Optimization of Monitoring Well Location for CO\textsubscript{2} Leakage Detection in GCS

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I. Abstract
Capture and sequestration of CO\textsubscript{2} in deep geological formations is an attractive option to reduce the amount of CO\textsubscript{2} emissions into the atmosphere. The capture of CO\textsubscript{2} is mostly done at large stationary point sources, such as power plants and refineries, and then it is injected in deep saline aquifers or old oil and gas fields. One of the environmental and policy concerns with this strategy is the potential of injected CO\textsubscript{2} to leak back to the atmosphere through abandoned oil and gas wells or to leak into underground sources of drinking water that can create other environmental problems. A risk management option is to place pressure-monitoring wells in overlying geological formations in order to detect changes in the pressure field that can come to occur due to leakage. The monitoring strategy becomes a question of optimization that tries to answer the question of how many wells to place and where to place them. In order to address this specific problem this study proposes a methodology that incorporates the use of a computational model that is run under a Monte Carlo scheme, a multi-objective evolutionary algorithm (MOA) and the use of a discrete static Kalman Filter (KF) to evaluate different objectives to be optimized. The computational model used simulates flow across 10 leaky wells and two geological formations, and the MOA evaluates using the KF the combinations of well number and locations. The two objectives considered in this study are the reduction of (1) the number of wells and (2) the total coefficient of variation (CV). For this study two cases were run. In the first case, the potential leakage well locations are considered to be known but with unknown permeability; the results show that the uncertainty can be completely reduced when using 10 monitoring wells (or more) but a substantial reduction is attainable with only 5 wells – uncertainty reduction of 64%. Simulation results also show that the placement of 10 monitoring wells does not really matter and that any location would reduce the uncertainty due to the high spatial correlation among wells. For the second case, the potential leaky well locations, as well as their permeability, were considered to be unknown. This case showed that the uncertainty is reduced only by 67% with 10 wells and that the placement of the wells follows a more balanced symmetric distribution. In this second case, after the placement of 5 wells the marginal reduction in uncertainty is minimal. Overall, this methodology strengthens the justification for the use of monitoring wells in overlying formation to detect leakage pathways associated with geological carbon sequestration, and it also provides an insight on the appropriate design protocol that can be used.

Keywords: Geological Carbon Sequestration, Monitoring Wells, Multi-objective evolutionary algorithm, NSGA-II

1. Introduction
Geological Carbon Storage (GCS) is one of the plausible options that could be implemented to reduce the Greenhouse Gas Emissions (GHG) to the atmosphere [1]. This technology entails injecting buoyant pressurized supercritical CO\textsubscript{2} into deep geological formations for long term storage. However, there exists a paradoxical opportunity given the century-long oil and gas explorations which have allowed the accumulation of vast geological information that permits for accurate design of CO\textsubscript{2} injection operations, but this knowledge comes at a cost of potential leakage through these old wells (Figure 1 represents the potential leakage).

In order to manage the risk of any leakage, as well as creating an accurate inventory of emissions reductions, certain regulations [3] require that pressure-monitoring wells be placed in overlying permeable formations in order to detect any pressure anomaly. The measurement of pressure as surrogate of CO\textsubscript{2} leakage detection has been presented before [4] as plausible means of risk assessment given that it has several advantages, namely the fact the measurements are done in situ and are continuous, and detection of an anomaly allows for quick response before any leakage of CO\textsubscript{2} or brine might reach overlying formations.

The obvious question that arises from this monitoring proposition is how many pressure-monitoring wells are needed and where to place them. To answer this questions there are several analogies that could be taken from the similar situations seen in sampling networks of shallow aquifers [4,5]. This study proposes the use of a computational model, a discrete static Kalman Filter (KF) and the use of a multi-objective evolutionary algorithm (MOA). In this study we propose to evaluate two objectives in order to optimize location of wells: The number of monitoring wells and the reduction in model uncertainty. For our study we define the uncertainty as the total sum of the standard deviation of pressures at each location divided by the mean at the same location – this value is known as the coefficient of variation.
Figure 1. Schematic representation of the process of CO\textsubscript{2} storage into deep geological formations. The largest unknown in this system is the leakage pathway permeability (i.e. well conductivity). There are numerous ways CO\textsubscript{2} can leak across the layers, given that CO\textsubscript{2} is more buoyant than the native brackish water. One option to reduce risk of leakage is to monitor for pressure changes in overlying formations. Figures made from previous publications [2].

2. Methodology

Prior to the evaluation of the monitoring locations a computational model is run under a Monte Carlo scheme to simulate different pressure propagation fields associated with leakage events. These pressure propagation fields are representation of different random realizations of leaky well permeabilities that are assigned to each passive well. The pressure fields are then used to calculate the covariance field over the entire simulation space. This covariance matrix, as is shown in Figure 2, is used as an input value in the MOA scheme. The multi-objective algorithm evaluates two objectives, the number of wells proposed and the reduction of the total variance associated with pressure field. The variance reduction is done through the use of the discrete static KF that updates the covariance matrix.

The KF is an optimal estimator that processes new information to update state variables by utilizing prior knowledge of the system, measurement error, and the initial condition as explained [6] – derivation of KF can also be found in this reference. In our case the update is done on the covariance matrix using the discrete static KF defined as,

\[
C(+) = [I - KH]C(-)
\]  

(1)

where \(C(-)\) and \(C(+)\) are the covariance matrix before and after the measurement is done respectively, \(H\) is the measurement vector which is represented by a chromosome from the MOA, \(I\) is the identity matrix and \(K\) is the Kalman Gain matrix defined as

\[
K = C(-)H^T[HC(-)H^T + R]^{-1} \tag{2}
\]

where \(R\) stands for the measurement variance matrix that in our study we assume is zero. The KF is used for model correction by filtering new information (measurements) and propagating this measurement across the field of state variables. In our study, the hypothetical measurement of pressure updates the covariance matrix in the specific location by updating the variance to zero in that particular location, but through the Kalman Gain it also updates the covariance matrix in other locations. The sum of the diagonals of the new covariance matrix, \(C(+)\), is used as the metric for uncertainty reduction.

Figure 2. Schematic representation of the evaluation scheme showing the combination of the Mathematical model, the Evolutionary Algorithm (NSGA-II) and the Kalman Filter. The H vector is derived from the chromosome proposed by the MOA.

2.1. Computational Model

The computation model used in this study is an analytical solution proposed by [7] that is able to simulate pressure propagation...
across geological formations. The pressure change is propagated through wells that are defined by a radius, length and permeability. The model is able to analyze practical injection problems in fast computational manner since it only solves equations relating to single-phase flow. The lack of accounting for the secondary phase (CO₂) does not affect significantly the calculation of the pressure propagation given that the pressure perturbation moves faster and much farther away than the potential CO₂ plume. Previous studies [4,8] have shown that the pressure propagation footprint is tens of hundreds of times larger than the associated CO₂ plume.

Figure 3a shows in schematic form what the mathematical model simulates. The geological formations, in layered form, are specified by their depth, thickness, and permeabilities and the model simulates the pressures in each layer with respect to the leaky wells. The model distinguished between passive (leaky) wells and injection wells. Figure 3b shows the location of the injection and leaky wells on top of the pressure perturbation in the monitoring formation created by one of the realizations.

![Figure 3](image)

Figure 3. a.) Schematic representation of the mathematical model used in the study. The CO₂ plume shown in the figures is not modeled explicitly. Here the pressure perturbation precedes any CO₂ and therefore the proposal is to measure pressure instead of CO₂. b.) Results from a sample simulation of the model that shows the pressures in the monitoring formation (in meters) after 5 years of injection. Figure 3b also shows the location of the injection well and the leaky wells.

2.2. Multi-objective Algorithm

In order to evaluate each alternative a fast and elitist multiobjective evolutionary algorithm known as NSGA-II [9] is used. The main advantage of using NSGA-II relies on the fact the MOA can propose solutions to highly non-linear systems and non-convex search spaces. The MOA is able to distinguish between chromosomes that are non-dominated by others and ranks them accordingly in order to pass them to the next generation.

Figure 4 portrays the overall MOA scheme where an initial population is created (in our case 100 chromosomes) then sent for evaluation of the two different objectives. The fronts are placed in a new population (P_{i+1}) created based on the criteria non-domination and crowding distance. The selection of two chromosomes is done randomly in order to do the cross over and the mutation. Once the new population, Q_{i+1}, is created it is joined with the previous population, P_{i+1}, and the process begins again.

![Figure 4](image)

Figure 4. Schematic representation of the NSGA-II algorithm used to evaluate the different objectives. Each combination of parent chromosomes produces one child. Crowding distance is used to evaluate a "tie" between two competing chromosomes.

2.3 Computational Model Specifics

The mathematical model was built using data gathered from the Alberta Basin in Canada and reported in [10]. The model simulates injection for 5 years into the Nisku formation and the pressures area calculated for the Wabamun formation, which overlies the Nisku formation as presented in Figure 3a. The time period of simulation was chosen to coincide with the U.S. Federal Requirements under the Underground Injection Control (UIC) program, which specifies a reevaluation of the area of review for injection operations every 5 years at a minimum. The area of simulation chosen for the 5-year simulation in this study was proposed in [4] given that the pressure pulse does not exceed 10 km from the injection area. Using data reported in [10] it was known the location of 10 old and abandoned wells (see Figure 3b) that go through the Wabamun and Nisku formation, in the area chosen to run the simulation.
For this study the computational model simulated injection into the Nisku formation 1881 m below the surface. The permeabilities assigned and the formation thicknesses are the same as reported in [4], as well as the injection rates, densities, viscosities, compressibilities, and widths of the permeable formations and the impermeable aquifer. For each realization the permeabilities assigned were randomly selected from log-normal distribution with mean -12.5 and variance 1 – permeability values were not allowed to go below -18 or higher than -7. More specifics on the injection and monitoring layers can be found in [11].

For this study two cases were run, in the first case as mentioned before the leaky well locations are known but the well permeability is taken to be uncertain. In the second case both the location and well permeabilities are taken to be uncertain. The number of wells as well all the other parameters considered are not changed. The construction of these two cases implies that the first Monte Carlo scheme was run over 1,000 realizations while the second were run over 10,000 simulations in order to obtain the initial covariance matrix.

5. Results and Discussion
The results for the first case, illustrated in Figure 5, show the initial Pareto and the final Pareto fronts. The reduction in uncertainty is expressed as a ratio of the final summation of the Coefficient of Variation (CV) over the initial summation of the Coefficient of Variation (CV_i). At first glance at Figure 5a it can be seen that as the number of monitoring wells is added to the system the measure of uncertainty reduces to zero. The case with ten wells (Figure 5f) indicates that independent of their location, ten wells completely eliminate the uncertainty in the model. This finding makes sense given that the total number of leaky wells is 10; therefore 10 monitoring wells should be able to capture all the uncertainty in the case where the leaky wells are static.

Another interesting finding from Figure 5a is that placing monitoring wells at any location reduces the uncertainty substantially. The MOA optimizes for each number of wells chosen but if the MOA were to be run again a different combination of locations would be picked. This implies that the setup of the model lends itself to multiple optimal locations. This is however inherent in the use of an evolutionary algorithm, which does not guarantee the best solution but one that approaches it asymptotically. In the particular case shown in Figure 5a the largest gain in uncertainty reduction is seen with the case of 6 monitoring wells.

Finally Figure 5 also shows that each combination of wells has a different setup (i.e. x-y location) and that it does not follow any typical geometric scheme around the injection well, especially as the number of monitoring well increases. With 2 and 3 monitoring wells some form of geometric distribution is seen, however with 4 or more wells any geometric distribution is lost. This also could be explained due to the fact that as the number of monitoring wells increases the reduction in uncertainty becomes independent (in some form) of the location of the monitoring wells due to the high correlation among leaky wells and the pressure perturbation field.

![Figure 5](image)

Figure 5. a.) Representation of the Pareto front (before and after) and the proposed monitoring well locations when optimizing 2 objectives (Coefficient of Variation and number of wells). Figures 5b through 5f show the location of the monitoring wells (filled circles) that reduced the measure of uncertainty the most for 2, 3, 4, 8 and 10 wells, respectively, overlaid on top of the average pressure field.

In the second set of simulations ran the leaky well locations and there permeabilities were considered to be uncertain. Figure 6a shows the initial and final Pareto front. In this case the reduction in uncertainty never reaches zero, even with 10 monitoring wells. Moreover, it seems that marginal gain in uncertainty reduction starts decreasing after 6 monitoring wells. The maximum reduction in model uncertainty is of 67%.

It is also clear from Figure 6a that the MOA offers substantial gain in uncertainty reduction compared to the first case. The final Pareto (i.e. hypervolume) is distinctly different from the original Pareto front. This indicates that there are not as many optimal positions to place monitoring wells as there were in the first case. Again, this can be explained through the loss in spatial correlation of the leaky wells.

Finally, Figures 6b through 6f show the optimal positions of the monitoring wells. Given the concentric shape of the average pressure field it is expected that the monitoring wells chosen by the MOA follow a geometric distribution of sorts. This can be seen for cases of 2, 3 and 4 wells clearly, Figures 6b, 6c and 6d, respectively. However, just like in the first case, as the number of
monitoring wells increases their location lose any geometric distribution, as seen in Figure 6e and 6f; yet they are more evenly distributed compared to the first case (comparison between Figure 5f and 6f).

6. Conclusions and Future Work

It was shown that the use of computational model, a MOA and a Kalman Filter as an evaluation function, can be used to determine the appropriate design of a monitoring network for a GCS operation. This methodology can allow policymakers and technocrats the ability to pick and choose from different options given the level of risk – in this study represented by model uncertainty – that one is willing to take. The two cases presented also show the importance of knowing the locations of the potential leaky wells. In our study we show that given the knowledge of leaky wells, the model uncertainty can be reduced to zero, while if that is not known the maximum reduction that can be reached is of 67%.

The first case in this study also shows the limitation of the modeling scheme proposed: For instance in the first case it is shown that the MOA improves on the original Pareto front only marginally given the high spatial correlation among leaky wells. We showed that regardless of the location of the monitoring wells once the number of monitoring wells approached the number of leaky wells the uncertainty dropped to zero independent of their location.

In order to truly exploit the power of the MOA, a more complex scheme could be considered; for instance, one that considers space-time covariance as proposed in [5]. The modeling could also include more uncertainty by including a realistic scenario of not knowing the permeability of the formations, number of injection wells and rates, and how many leaky wells are present – in this study the number of leaky wells were maintained at 10. In the same line the MOA could be expanded to include more than two objectives such as the minimization of the total standard deviation of the model, minimize the maximum variance, minimization among the minimum and maximum variance, and the minimization of the variance of the area influence of each monitoring well, among other objectives to be identified.

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8. References

