RAPID OPTIMISATION OF THE NEW SLEIPNER BENCHMARK MODEL

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Abstract

A new Sleipner benchmark model has recently been released. Basic petrophysical parameters are included in the dataset but it is intended that further modelling work should be carried out in order to refine parameter estimates. In this study we have developed a rapid calibration workflow, in the open source Matlab Reservoir Simulation Toolbox (MRST). We use this workflow to calibrate model parameters such that results match plume outlines interpreted from seismic data, also provided in the benchmark dataset. This is made feasible by the use of hybrid vertical equilibrium (VE) modelling and adjoint-based, continuous optimisation, using automatic differentiation. Parameters have been found which lead to simulation results that provide a reasonable match to the plume outline in the top layer, when using a slightly modified model top surface. This workflow provides a useful tool which allows us to use monitoring data to improve simulation models during and after CO_2 injection.

Keywords: *Sleipner, Vertical Equilibrium, Optimisation, MRST, Reservoir simulation*

1. Introduction

Underground CO_2 storage has been undertaken at the Sleipner site since 1996. During this time a whole host of geophysical monitoring data, in particular seismic data, has been collected from the site, allowing us to infer information about the temporal evolution of the CO_2 plume as well as information about the internal structure of the reservoir. Importantly, seismic observations of the CO_2 plume reveal a more detailed picture of the layered internal structure of the reservoir [1].

In conjunction with geophysical monitoring data we can use simulations to better understand the dynamic processes occurring in the subsurface and reduce uncertainties in simulation parameters (e.g. model geometry, petrophysical parameters). Initial simulation work at Sleipner involved simplified models with basic geometry to investigate the layered structure and CO_2 plume migration [2].

In 2011 a Sleipner benchmark model was released, with realistic geometry inferred from seismic data [3]. This model covered the uppermost layer of the reservoir, layer 9, where we have the most accurate seismic coverage.

Several studies used this model as a starting point to identify parameters which give simulation results that best match the CO_2 spread at the top of the reservoir, identified in the seismic data [3] [4] [5] [6]. As this benchmark only comprises the top layer of the reservoir, assumptions have to be made regarding the amount of CO_2 in the layer and the location it is first introduced into the model.

These studies generally showed the strong influence of the permeability heterogeneity and the topography of the top surface on the resulting plume shape but several things are still debated. For example the mass distribution within the layers, the density of the plume and the vertical migration mechanism through the shale layers, capillary flow vs higher permeability pathways.

A new Sleipner benchmark model was released by Equinor in 2019 [7]. It includes an updated reservoir model which covers the whole depth of the reservoir including the injection well. It also contains supplementary information such as injection rates, the suspected location of possible feeder chimneys through the shale, based on the changes in the nature of the seismic signal, and the extent of the plume at the top of each layer after 15 years injection, also based on the seismic data.

The base model has been populated with a basic set of parameters (uniform permeability and porosity for the sand, uniform permeability and porosity for the shale) which can be used as a starting point to determine a more realistic parameter set.

In this study we have developed a rapid optimisation workflow which uses hybrid vertical equilibrium modelling [8] and adjoint-based continuous optimisation to run simulations on the new benchmark model and find more realistic parameters, constrained by the observed data. Here we have used the plume outlines given in the dataset as the data we would like to match our simulations to. Further work has been undertaken in [9] where multiple types of monitoring data have been used in combination to further constrain the reservoir parameters.

Simulations have been carried out using the Matlab Reservoir Simulation Toolbox (MRST) [10]. MRST is open source and highly flexible allowing for rapid prototyping and easy modification of model equations. It also contains functionality for vertical equilibrium modelling and gradient-based optimisation using adjoints.

The combination of the hybrid VE framework with adjoint based optimisation and automatic differentiation is key to allowing us to run automatic optimisation, with a flexible objective function, on a model as large as the

Sleipner benchmark (~1.9 million cells in the original benchmark simulation grid).

2. Methodology

2.1 Governing equations

We use the equations for multiphase flow in porous media and a finite-volume discretisation. The mass conservation of phase α is given by:

$$\frac{\partial(\phi \rho_\alpha s_\alpha)}{\partial t} = -\nabla \cdot (\rho_\alpha \boldsymbol{u}_\alpha) + \rho_\alpha f_\alpha \qquad (1)$$

where ϕ is porosity, ρ_α is phase density, s_α is phase saturation (volume fraction), f_α is the sum of any sinks / sources and $\boldsymbol{u}_\alpha$ is the Darcy flux of phase α. The multiphase equation for the Darcy flux is:

$$\boldsymbol{u}_\alpha = -\frac{\mathbf{k} k_{r\alpha}}{\mu_\alpha}(\nabla P_\alpha + \rho_\alpha \boldsymbol{g}) \qquad (2)$$

with permeability $\boldsymbol{k}$, relative permeability, which is a function of the wetting phase saturation $k_{r\alpha} = k_{r\alpha}(s_\alpha)$, phase viscosity μ_α, phase pressure P_α and gravity vector $\boldsymbol{g}$. All phase saturations sum up to unity.

2.2 The hybrid vertical equilibrium model

The hybrid VE model is a modification of the standard VE model and is described in detail by [8].

In the standard VE model we solve a form of the governing equations which have been integrated vertically such that we are solving for the vertically integrated horizontal fluxes in the model. The vertical configuration of fluids can then be calculated from the results based on the assumption that fluids in a grid cell have reached vertical equilibrium. Thus we do not need to discretise the model in the vertical direction, leading to a large reduction in the number of grid cells required. This method has been shown to work well for systems with large buoyancy contrasts such as brine-CO_2 systems [11] [12].

The internal layering of the new benchmark model requires a modification to this method. Here, the layers are in vertical equilibrium internally but there is still flux between layers and up through the reservoir. As a whole, the reservoir is not vertically equilibrated due to the low permeability shale layers, as indicated by the layered structure of the CO_2 plume seen in the seismic data.

The hybrid VE framework we have used allows us to have a hybrid grid, with volumes being modelled as VE cells connected to volumes modelled as fully resolved cells (normal 3D simulation). This means we can setup a simulation grid which uses VE simulation internal to each layer but which has fully resolved cells that represent the possible feeder chimneys and allow us to model vertical flow at these locations.

2.3 Model setup

The benchmark simulation grid contains approximately 1.9 million cells. We convert the 9 sandstone layers in the grid into a series of stacked VE layers with impermeable boundaries between the layers to represent the low permeability shales. There are fully resolved cells in the locations of the suspected feeder chimneys (Fig. 1). In total the hybrid VE grid contains 76527 cells, which is about 4 percent of the original cell count.

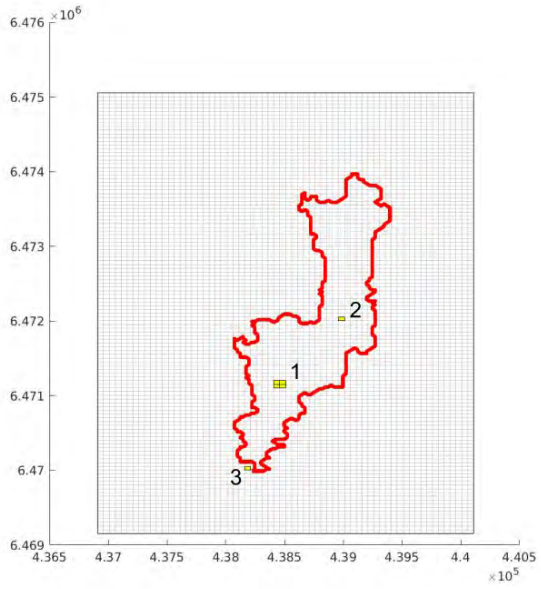

Figure 1: The three possible feeder locations included in the dataset. Red line is the plume outline at the top of layer 9. Numbers 1, 2 and 3 correspond to the permeability factors shown in Fig. 6. The main feeder chimney can be identified on the seismic data and intersects the whole of the reservoir up to layer 9. The other two chimneys are less clear in the seismic data and intersect only layer 5 and layer 7 respectively.

The location of the injection well is taken from the benchmark dataset. Injection rates are given in [13].

Petrophysical properties for the model are given in the benchmark dataset. Fluid properties for CO_2 are calculated based on temperature and pressure using the CoolProp library [14] [15]. Although temperature is not modelled in the simulation we impose a background temperature gradient with an injection temperature of 41 °C and a temperature at the top of the reservoir of 37 °C. Fluid properties are shown in Table 1.

Table 1. Simulation fluid properties.

Brine density [kg m^{-3}]	1020
CO_2 density [kg m^{-3}]	318 - 497
Brine viscosity [Pa s]	8.00×10^{-4}
CO_2 viscosity [Pa s]	6.00×10^{-5}
Brine compressibility [bar^{-1}]	4.37×10^{-5}
CO_2 compressibility [bar^{-1}]	4.37×10^{-4}

2.4 Adjoint based optimisation

Adjoint based optimisation is implemented in MRST as described in [5] [16].

The aim of the optimisation is to update model parameters so that simulated plume outlines match the plume outlines given in the benchmark dataset. Plume outlines, provided as polygons, show the extent of the CO_2 plume at the top of each layer in the 2010 seismic survey. The objective function, J_{plume}, is given by:

$$J_{inside,i} = \left(\frac{h_i - h_{min}}{H_i - h_{min}}\right)^2, \quad h_i < h_{min}$$

$$J_{inside,i} = 0, \qquad h_i > h_{min}$$

$$J_{outside,i} = \left(\frac{h_i - h_{min}}{-h_{min}}\right)^2, \qquad h_i > h_{min}$$

$$J_{outside,i} = 0, \qquad h_i < h_{min}$$

$$J_{plume} = \sum_i J_{inside,i} + \sum_i J_{outside,i} \qquad (3)$$

where h_i is the height of CO_2 in cell i, h_{min} is the assumed minimum CO_2 column height required for the plume in that cell to be visible in the seismic data and H_i is the total height of cell i.

We have chosen individual layer and chimney permeabilities, porosity and CO_2 density as the parameters to be optimised. Varying the parameters is carried out by multiplying them by a scalar value which is allowed to vary within a certain range. The ranges for porosity and permeability are chosen based on the range of values given in the dataset.

We have chosen to vary the CO_2 density as there is some uncertainty in the temperature distribution in the reservoir which may have a large impact on the density distribution in the plume.

3. Results

3.1 Matching the benchmark model

Fig. 2 shows the simulated CO_2 saturation after 15 years injection for the unoptimised benchmark model. Plume outlines from the benchmark data are shown in red. Using the base case model does not give a good match between the observed and simulated plume outlines.

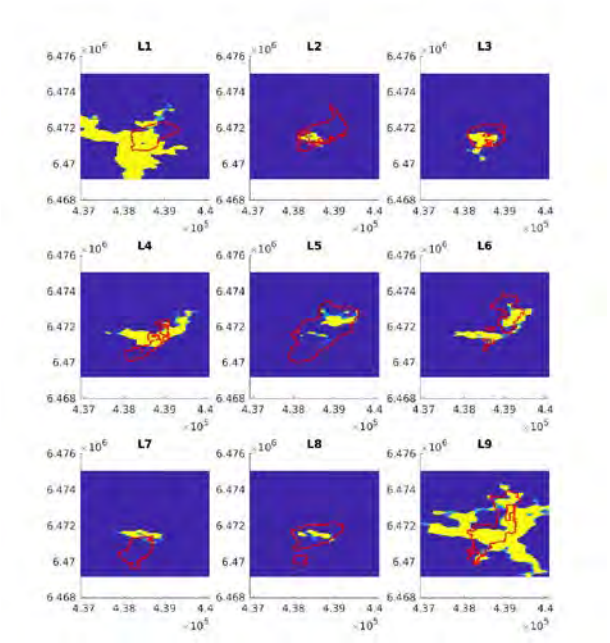

Figure 2: CO_2 saturation at the top of all layers. Unoptimised benchmark model. Plume outlines from the benchmark are shown in red.

After running the optimisation, where we are only concerned with matching the outline in layer 9, we find that we are still unable to get a good match between the simulated plume in layer 9 and the plume outline (Fig. 3).

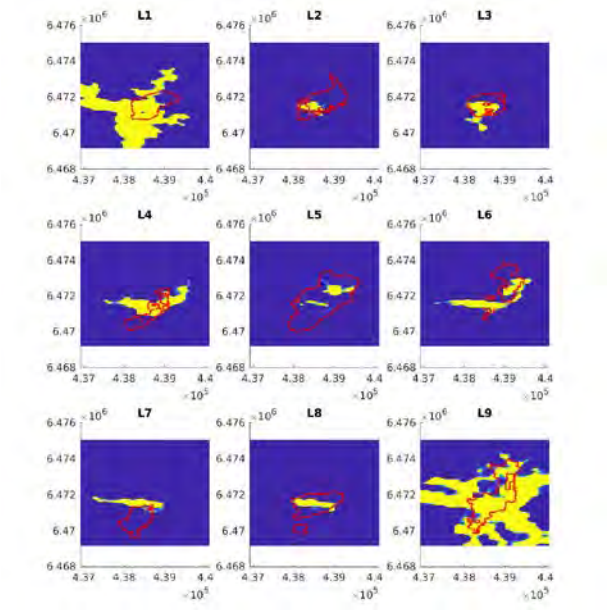

Figure 3: CO_2 saturation at the top of all layers. Optimised model matched to plume outlines in layer 9. Plume outlines from the benchmark are shown in red.

Consistent with previous studies, all our simulations lead to outcomes where CO_2 collects locally as a plume beneath each vertical flow barrier, with a shape that closely reflects the shape of the overlying confining layer. Closer inspection of the topography of the top layer

of the model (Fig. 4) shows that it is incompatible with the plume shape and therefore it is impossible for us to match the plume shapes with the topography that we have.

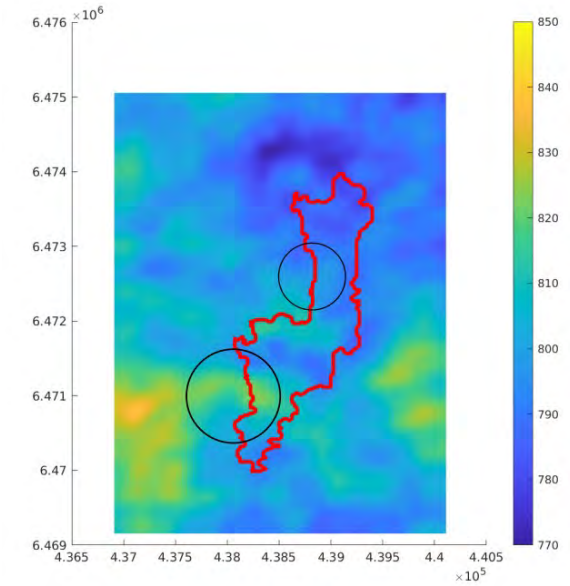

Figure 4: Depth of top surface of the benchmark model with plume outline for layer 9 on top. Notice the bottom circle shows a dip in the surface which cuts across the plume edge. A similar feature can be seen in the top circle. If these areas are to be covered by the plume then CO_2 will also be able to migrate outside of the plume outline, as happens in Fig. 3.

3.2 Modified top surface

Based on past studies which have had some success matching the plume outlines in the older benchmark model [5], we have adjusted the top surface of the new benchmark model such that it has the same topography as the older model given in [3]. Each column of grid cells has been shifted by a certain amount, this means all layers are affected by the shift in the vertical direction.

Results from matching to the layer 9 plume with the modified top surface are greatly improved although there is still some CO_2 outside of the plume outline (Fig. 5). We also see much better results for plume shapes in the underlying, internal layers even though matching plume outlines lower down the reservoir was not included in the objective function of this particular optimisation.

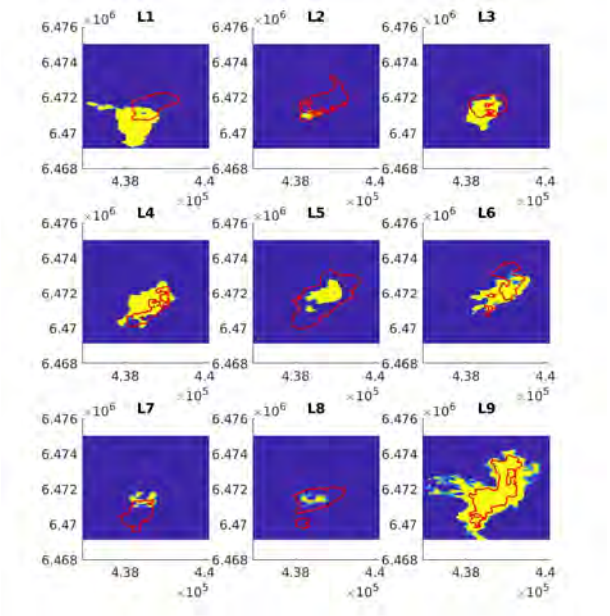

Figure 5: CO_2 saturation at the top of all layers after 15 years injection with the modified top surface. Optimised model matched to plume outlines in layer 9. Plume outlines from the benchmark are shown in red.

Looking at the resulting optimisation factors (Fig. 6, row 2) shows an increase in CO_2 density and a reduction in permeability for the main feeder chimney, this reduces the amount of CO_2 reaching the top of the model and makes it spread out less. However, this is also in conjunction with an increase in permeability in layer 9 which will conversely make the CO_2 spread out more. It is the interplay between all these factors, as well as the topography of the layer, which controls the geometry of the plume. In this way, it is possible that the result, in terms of optimisation factors, could be ambiguous. We could reduce the uncertainty by constraining with other data such as gravity measurements or specified mass in each layer [15].

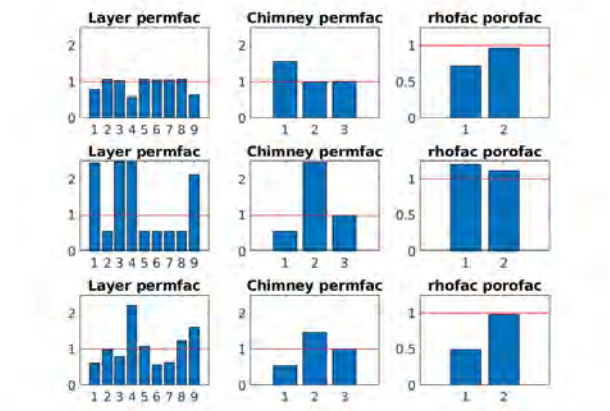

Figure 6: Optimised parameter factors. From top to bottom the rows pertain to: Matching layer 9 with the benchmark top surface, Matching L9 with the modified top surface, Matching all layers with the modified top surface.

We also observe an increase in permeability for chimney 2 which is in the north-eastern part of the reservoir between layers 5 and 6. This suggests that more CO_2 is required in the in the north-east part of the plume in layer 6 to fit the plume outline better.

Our modelling framework allows us to specify which individual outlines we would like to include in the optimisation. Fig. 7 shows the results when we optimise to fit plume outlines in all layers. Here the match in lower layers is improved compared to Fig. 5 at the expense of the match in the top layer. As there is much greater uncertainty in the outlines in lower layers, being able to get a good match to outlines in all layers is relatively unrealistic.

Matching to plume outlines is only possible if the topography of the model is compatible with their shapes. This means that we cannot hope to obtain a close match without being able to modify the actual model geometry. Arguably the plume outlines only provide limited information on the CO_2 spatial distribution. Although corresponding z coordinates are given, these are not of much use as they do not generally correspond to the topography of the surface. For more detailed information about CO_2 migration we require a better measure of how the mass of CO_2 is distributed in the plume.

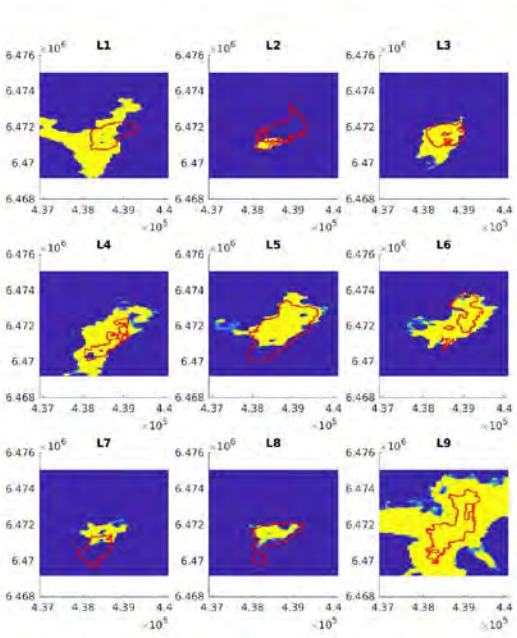

Figure 7: CO_2 saturation at the top of all layers after 15 years injection with the modified top surface. Optimised model matched to plume outlines in all layers. Plume outlines from the benchmark are shown in red.

3.2 CO_2 mass distribution

Fig. 8 shows that for both optimisations we reduce the CO_2 mass in the top layer from the unoptimised case. There is some redistribution of CO_2 in the layers in the middle of the reservoir (layers 3, 4, 5, 6). For fitting all plumes we see increased CO_2 mass in layer 5 compared to fitting only the layer 9 plume, this is where the optimisation algorithm tried to fit the larger plume outline of layer 5.

In [17], the authors tried to estimate CO_2 mass in each layer. In the future it would be interesting to use our model and attempt to match a certain CO_2 mass in each layer as well as the plume outlines. This would be relatively easy to implement in our framework due to the rapid prototyping capabilities of MRST.

It should be noted that CO_2 mass is also closely connected to the density profile in the model. Here we have used an initial vertical density profile computed from local pressure and temperature using an equation of state, and then modified the density of CO_2 in the whole model using a single scalar multiplier. This will lead to slightly unrealistic estimates of plume density as CO_2 is highly non-linear in the region close to the conditions in the reservoir, i.e. a slight change in pressure and temperature can lead to a large change in CO_2 density. Also, the temperature at the injection well is fairly well constrained but there are large uncertainties in the temperature at the top of the reservoir and therefore in the temperature gradient. To investigate the density profile of CO_2 at Sleipner we should extend our model so that we can use the temperature gradient as an optimisation parameter instead of density.

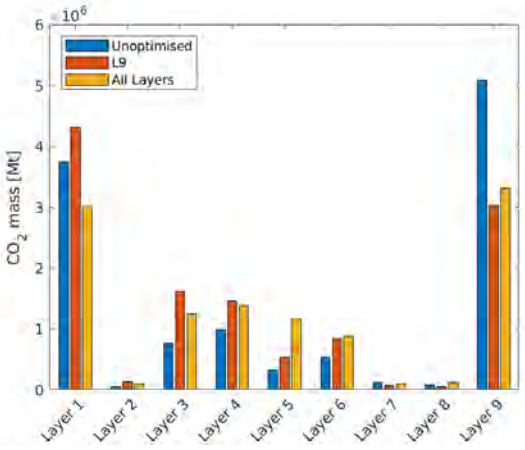

Figure 8: CO_2 mass in each layer when matching to different plume outlines.

4. Conclusions

We have used a hybrid VE model, implemented in the open-source code, MRST, to efficiently simulate the new Sleipner, multi-layered, benchmark model. A framework for rapid optimisation has been developed and we have optimised selected properties of the simulation model to match plume outlines given in the benchmark dataset. Closer inspection of the benchmark model shows that the topography of the surfaces is not compatible with the observed plume outlines, at least without significantly departing from the generally agreed assumptions of rapid gravity segregation and local CO_2 pooling. Results from modifying the geometry so that the top surface resembles the 2011 benchmark model show a closer match to the

plume although an exact match cannot be found without being able to modify the top surface automatically.

Being able to use more geophysical data in a combined fashion will allow us to better constrain the parameters we have and reduce the ambiguity in optimisation results.

Future work should also focus on investigating the temperature and therefore density profile of the plume which may help our understanding of vertical migration within the reservoir.

In general, this workflow can provide a valuable tool to integrate monitoring data acquired during and after CO_2 injection into dynamic simulation models. Thereby improving the accuracy of the simulation models and helping to elucidate processes occurring in the subsurface.

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