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A machine learning based monitoring framework for CO2 storage

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With increasingly visible effects of climate changes and a growing awareness of the possible consequences, Carbon Capture and Storage (CCS) technologies are gaining momentum. Currently preparations are being done in Norway for a full-scale CCS project where CO_2 will be stored in a deep saline aquifer. A possible candidate for such storage is Smeaheia, located in the North Sea.

One of the main risks related to large scale storage projects is leakage of CO_2 out of the storage complex. It is important to design measurement, monitoring and verification (MMV) plans addressing leakage risk together with other risks related to conformance and containment verification. In general, geophysical monitoring represents a significant part of storage monitoring costs. Tailored and cost- effective geophysical monitoring programs that consider the trade-off between value and cost are therefore required. A risk-based approach can be adopted to plan the monitoring, but another more quantitative approach coming from decision analysis is that of value of information (VOI) analysis. In such an analysis one can define a decision problem and measure the value of information as the additional value obtained by purchasing information before making the decision.

In this work, we study the VOI of seismic data in a context of CO_2 storage decision making. Our goal is to evaluate when a seismic survey has the highest value when it comes to detecting a potential leakage of CO_2, in a dynamic decision problem where we can either stop or continue the injection. We describe the proposed workflow and illustrate it through a constructed case study using a simplified Smeaheia model. We combine Monte Carlo and statistical regression techniques to estimate the VOI at different times. In a first stage, we define the decision problem. We then efficiently generate 10000 possible distributions of CO_2 saturation using a reduced order-based reservoir simulation tool. We consider both leaking and non-leaking scenarios and account for uncertainties in petrophysical properties (porosity and permeability distributions). From the simulated saturations of CO_2, we derive distributions of geophysical properties and model the corresponding seismic data. We then regress those values on the reference seismic data, to estimate the VOI. We evaluate the use of two machine learning based regression techniques- the k-nearest neighbours' regression with principal components and convolutional neural network (CNN). Both results are compared. We observe that VOI estimates obtained using the k-nearest neighbours' regressions were consistently lower than the estimates obtained using the CNN. Through bootstrapping, we show that the k-nearest neighbours approach produced more stable VOI estimates when compared to the neural networks' method. We analyse possible reasons of the high variability observed with neural networks and suggest means to mitigate them.

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