Porosity estimation by neural networks for CO₂ storage in Otway site

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Abstract Dynamic simulation of CO₂ migration requires a variety of modeling parameters fed by geomechanical models. The confidence of these parameters of material groups such as porosity and permeability is crucial in achieving successful simulations. Based on the geomechanical and geophysical parameters, we estimated porosity distributions on the Paaratte Formation in the Otway site, one of the CO₂ storage project in Australia. Considering the non-linear relations between porosity logs and seismic data, we applied the neural network scheme that addresses the porosity value across a whole domain. With only one monitoring well and two injection wells at the site, seismic data are used to restore the spatial absence in porosity. The technique of the neural network was conducted based on the integration of the well logs to the seismic volume and the inversion of acoustic impedance. The results indicated that a correlation value of the well and the seismic tie is 75% and the value between the recorded and the estimated porosity is 87% on average. Further, the time slice maps of porosity at a depth of the injection interval demonstrated a CO₂ plume developed in the Paaratte formation of the Otway site.

Article Highlights

- This study derived the porosity of subsurface on the Otway project for monitoring and simulating CO₂ stored in the subsurface.
- The present methodology of neural network is based on the correlation between well log and seismic exploration data.
- The result of porosity distribution shows that the integration of geomechanical and geophysical properties can embody the understandings of CO₂ in the storage formation.

Keywords Porosity · CO₂ storage · Seismic data · Neural network · Otway site

1 Introduction

Carbon Capture and Storage (CCS) can mitigate a global warming problem caused by Greenhouse gases. Conventionally used in an operating reservoir through the Enhanced Oil Recovery (EOR), CO₂ among the greenhouse gases can be disposed at depleted hydrocarbon reservoirs or saline aquifers massively. Sand dominant saline aquifers can be
excellent storage for CO₂ disposal (Arts et al. 2004). One of the representative CCS research is the Otway project to demonstrate CO₂ storage which set up to three stages of feasibility, verification and stabilization studies (Dodds et al. 2009; Pevzner et al. 2017a; Jenkins et al. 2021). In the first stage, the project chose a depleted gas reservoir for site assessment of the Waarre C Formation at a depth of 2000 m to seek a favorable porosity and permeability condition for CCS (Sharma et al. 2011). Experience in monitoring and verifying the injected CO₂ in the first stage suggested that they seek the possibility of injecting and monitoring CO₂ to aquifers as well (Jenkins et al. 2012). Thus the Otway project established the second stage with an additional injection of CO₂ to a saline aquifer about 1400 m depth in the Paaratte formation (Pevzner et al. 2015, 2017b). Otway project entered third stage which is matured step with confirming stabilization of stored CO₂ (Correa et al. 2018; Isaenkov et al. 2021). The Otway Project is establishing itself as a representative project for CCS by installing additional boreholes and testing cutting-edge technology in an ongoing process.

In the site characterization of the second stage, an experimental study confirmed the need for precise information about subsurface in the Otway field (Sharma et al. 2009; Pevzner et al. 2013). Due to the limited number of wells drilled for this purpose relative to the physical dimension of the field, insufficiency of field data is often a problem to achieve an accurate description of the subsurface. To resolve the problem, Dance et al. (2009) investigated several techniques applied in the site characterization. Based on the high-quality monitoring data produced by the Stage II Otway Project, additional geological characterization and geomechanical analysis are ongoing (Mishra et al. 2019; Tenthorey et al. 2019). Because researches on the application of simulations using geological and geomechanical models are active, the need for accurate geophysical information is still high. Typically, sedimentologists construct a static model with facies analysis resulting in a reasonable estimation of porosity and permeability. This study present way of characterization using the probabilistic neural network (PNN) differs from the typical method dependent on the information of facies analysis.

Neural Networks (NNs) have been used in the field of geophysics over the past few decades inverting various parameters such as seismic, well logs and magnetotelluric data (Van der Baan et al. 2000). Although the NN has the limitation of mere pattern recognition, the advantage of the robust and cost-effective solution after computational implementation has made the NN an essential tool in the field of hydrocarbon exploration the oil industry. As NN has the capability of predicting inter-well information where enough well log data are not available, a further application to CCS sites is reasonable to help complete site characterizations (Poulton 2002; Tonn 2002; Pavlova and Reid 2010). Among the geomechanical parameters such as porosity, permeability, and the geometry, we derived porosity distribution using the NN. Porosity and permeability are both critical reservoir parameters. Conventionally permeability is defined concerning core-scale and upscaled to become anisotropic by nature. Because of isotropic nature of the porosity, we have chosen the porosity derived and verified with the NN to the reservoir scale. A further application to the permeability requires anisotropic seismic data limited in this study.

Still, the NN is useful when sufficient data accumulates as the number of sites increases. The potential of the NN with increasing data is phenomenal. Comprehensive data collected from the Otway site strengthens the reliability of the NN in this perspective. The present study aims to estimate the porosity distribution of CO₂ storage from seismic and well log data by applying the NN to the Otway project. The result in this study is a framework in which the proven NN method (Boult and Donley 2001; Leiphart and Hart 2001; Pramanik et al. 2004) is applied to the CCS research area. The current study can provide property models for the numerical simulation to monitor the behavior of the injected CO₂ further.

### 2 Field data preparation

In the Otway project, 66 kT and 15 kT of the CO₂/CH₄ mixture were injected into the Waarre C formation (depleted gas reservoir) and the Paaratte formation (a saline aquifer). Up to date, the study focuses on monitoring CO₂ within the Paaratte formation in the second stage (Urosevic et al. 2010). We confined a target interval of the Paaratte formation to compute the porosity for input of dynamic simulation. Then, NN calculates a nonlinear solution from the well log and seismic data and results
in reservoir parameters, i.e., porosity (Trappe and Hellmich 2000). Because the estimation of the NN depends heavily on the confidence of the target interval, the well log and seismic data should be validated to their accurate position and depth. Further, correlation of the well log and seismic data was also estimated to ensure the proper target interval.

2.1 Well log data

Until second stage, Otway project drilled two wells named by CRC-1, CRC-2 to inject and to monitor CO₂ disposal and converted one existing well of Naylor-1 for additional monitoring purpose. Figure 1 shows a map of the Otway project with well locations of Naylor-1, CRC-1, and CRC-2. Table 1 lists the well log depth interval and available properties of Gamma Ray (GR), density, P-wave impedance,

| Well name | Start (m) | Stop (m) | Date         | Gamma ray | Density | P-impedance | Porosity | Sonic |
|-----------|-----------|----------|--------------|-----------|---------|-------------|----------|-------|
| Naylor-1  | 20.0      | 2145.2   | 09-Nov-2011  | Logged    | Logged  | Logged      | Logged   | Logged|
| CRC-1     | 1000.2    | 1529.9   | 09-Nov-2011  | Logged    | Logged  | Logged      | Logged   | Logged|
| CRC-2     | 9.7       | 1554.0   | 09-Nov-2011  | Logged    | Logged  | Not available | Logged   | Logged|
porosity, and sonic data. CRC-1 is located in the center of the study area, and CRC-2 and Naylor-1 are approximately 170 m northeast and 280 m northwest apart from CRC-1.

In the formation that has radioactive minerals, a high GR reading occurs in the use of the GR for interpreting lithology/porosity. The neutron/density crossover is evaluated to prevent this interference in the GR reading. However, we did not consider the interference into the use of the GR to focus on the present inversion methodology itself in this study. Porosity log was acquired by pulsed neutron tool. Correction of neutron logging data is important consideration at CCS site regarding CO₂ residual saturation (Dance and Paterson, 2016). Since we investigate initial model condition, before CO₂ injection, the Paaratte formation would be less affected by lithology/porosity change. Therefore, GR and porosity logs are considered with consistent state.

The similarity of the GR log demonstrated a lateral consistency of the Paaratte formation between wells (Fig. 2). The Paaratte formation is an aquifer layer and lies below Timboon sandstone and above Skull Creek mudstone formation (Dance 2013). The Paaratte formation consists of deltaic and marine sediments of fine-to-coarse-grained quartz sandstones (Lebedev et al. 2013). The present analysis set the target interval of the seismic travel time between 900 and 1300 ms to include the Paaratte formation. We further refined the range between the horizons of the Paaratte top and the Skull Creek top at the next section of well-to-seismic correlation.

2.2 Seismic data

The Otway project conducted three-dimensional land seismic exploration on the Otway research site in January 2009. Table 2 briefs acquisition parameters of the seismic survey, representing a high resolution of 100 stacking folds. To record the reflection signal, 873 geophones were installed, and 2181 vibroseis sources produced the artificial seismic energy. The survey covers a 1.6 × 1.9 km area divided by 10 m grid rectangular bin. Poststack migrated volume is imported and validated whether the target domain locates appropriate depths for the well logs. The sample seismic section showed a horizontally consistent event for the Otway aquifer layer (Fig. 3). The picked horizons of the Paaratte top and the Skull Creek top appeared at the travel time of ~950 and 1200 ms respectively on the vertical axis of the seismic section. The geological structure laterally continued between the Naylor-1 and CRC-1 wells with characteristic reflection amplitude. We do not see
heterogeneity as a barrier for CO$_2$ injection between the wells at the target domain based on conformable geology (Dance et al. 2019).

We interpolated and extrapolated each horizon by tracing the seismic event into the entire area starting from the well log picks (Fig. 4). We interpreted the Paaratte top horizon at a depth of travel time between ~900-970 ms with greater depth in the northwest direction. The Skull Creek top spread out over 1150–1230 ms, indicating the base of the CO$_2$ injection domain. The picked horizons in the time-slice map demonstrated that the seismic data is reliable to determine a potential boundary of the CO$_2$ plume. Isochron maps at 944 and 1200 ms showed the distribution of each horizon. We confirmed the actual depth of the horizons of Paaratte top and Skull Creek top using the well-to-seismic correlation that shows the quantitative correspondence.

### 2.3 Well-to-seismic correlation

The precise correlation of the well log to seismic data would assure the particular application of the NN for porosity calculation in the Otway project. We estimated statistically seismic source wavelet from the seismic volume within the analysis domain and calculated reflectivity from the density log and the P-impedance log at each well location. The convolution of the source wavelet with reflectivity results in synthetic seismic traces compared with recorded seismic traces by peak and trough. In the Otway data, the correlation values between synthetic and recorded

| Parameter                     | Value            |
|-------------------------------|------------------|
| Survey type                   | 3D land          |
| Number of source lines        | 29               |
| Number of receiver lines      | 10               |
| Bin size (m)                  | 10               |
| Offset range (m)              | 50–2150          |
| Source line/point spacing (m) | 100/20           |
| Receiver line/point spacing (m)| 100/10       |
| Record length (s)             | 4                |
| Sample interval (ms)          | 2                |
| Nominal stacking fold         | 100              |

**Table 2** Seismic data acquisition parameter of the Otway project

![Cross-Sectional view of poststack seismic data estimated along the Naylor-1 and CRC-1 with inserted Gamma Ray log at the Naylor-1 (red solid line) and the CRC-1 (gray solid line) wells](image)

**Fig. 3** Cross-sectional view of poststack seismic data estimated along the Naylor-1 and CRC-1 with inserted Gamma Ray log at the Naylor-1 (red solid line) and the CRC-1 (gray solid line) wells
traces were 72.68, 70.86 and 82.89% for the well of Naylor-1, CRC-1 and CRC-2 respectively (Fig. 5). The major reflection events of the synthetic traces (blue) coincided with the recorded traces (red) within the analysis domain.

2.4 Probabilistic neural network (PNN)

The convolution operator of multiple attributes minimizes the prediction error by linear regression. However, the linear combination of the attributes could not resolve the non-linear problem prevalent in the well log property. The PNN method, proposed by Specht (1990), recognizes the pattern of non-linear solution using a hidden layer by finding the optimum weight function known as "training data" (Hampson et al. 2001). Based on the three well log data from the Otway site, screening processes has led the PNN method ahead of other optimization techniques. The present study used the PNN to correlate the several attributes for estimating the porosity of the Paaratte formation.

If we assume \( n \) training samples of \( x \) at a location having \( m \) attributes, we can write the estimated log (e.g., porosity) \( L(x) \) of the PNN as

\[
L(x) = \frac{\sum_{i=1}^{n} L_i \exp(-D_i)}{\sum_{i=1}^{n} \exp(-D_i)}.
\]  

(1)

In Eq. (1),

\[
D_i = \sum_{j=1}^{m} \left( \frac{x_j - x_{ij}}{\sigma_j} \right)^2.
\]  

(2)

where \( D_i \) is the distance between input and training points and \( \sigma_j \) is the smoothing parameter. To accomplish non-linear regression, PNN uses activation

Fig. 4 The extrapolation result of horizon picks. Time structure map of a the Paaratte top and b the Skull Creek top and iso-chron map of c 944 ms with red Paaratte top and d 1200 ms with yellow Skull Creek top. The Skull Creek top indicates the bottom of the Paaratte formation.
function with a smoothing parameter in this study. According to Specht (1990), the choice of activation function depends on computational simplicity, and the exact form of it is not critical to the effectiveness of the network. As smoothing parameter in Eq. (2) increases, the non-linear regression becomes smoother, but it may not fit the exact data point. Smoothing parameters are determined during
the training process in such a way that the resulting network has the lowest validation error (Hampson et al. 2001).

For the Otway site, Table 3 summaries the attributes used for the PNN with smoothing parameters. We calculated the P-impedance recursively from reflectivity, which is source-removed seismic data (Fig. 6). From the P-impedance, we can quickly calculate the P-wave by factoring density of material from the well log. For verification, we compared the predicted P-wave with the actual P-wave shown in the P-wave velocity cross-plot (Fig. 7). Finally, we estimated the porosity distribution of the Paaratte formation over the Otway area.

### Table 3 PNN attributes and smoothing parameters (sigma) estimated for the Otway site

| Attribute                        | $\sigma_{\min}$ | $\sigma_{\max}$ |
|---------------------------------|-----------------|-----------------|
| Dominant frequency of seismic data | 3.921           | 4.197           |
| P-impedance$^2$                 | 2.381           | 2.595           |
| Absolute amplitude of seismic   | 1.502           | 2.044           |
| Filtered seismic 15/20–25/30 Hz | 0.405           | 2.698           |
| Filtered seismic 45/50–55/60 Hz | 0.161           | 1.967           |
| Filtered seismic 5/10–15/20 Hz  | 2.195           | 2.523           |
| Cosine(instantaneous phase of seismic) | 0.337           | 4.116           |

### 3 Results and discussion

In this section, we verified the P-wave impedance by comparing the estimated and measured values via the P-impedance inverted from the seismic data. Further, we have compared the estimated porosity distribution with monitoring results qualitatively (Urosevic et al. 2010; Watson et al. 2012; Pevzner et al. 2017b).

#### 3.1 Verification of the P-impedance and the porosity log

Among the three wells on the Otway site, we depicted the cross-sectional view of the P-impedance estimated along the Naylor-1 and CRC-1 in Fig. 6. We interpolated the P-impedance between the wells in the vertical region delineated by the top (the Paaratte formation) and the bottom (the Skull creek). The estimated P-impedance was relatively high along the strong reflection at 1050, 1070 and 1120 ms adjacent to CRC-1 on the seismic section. High values of the

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**Fig. 6** Cross-sectional view of the P-impedance estimated along the Naylor-1 and CRC-1
P-impedance inferred sand-dominant sediment characterized by high reflectivity. Despite a small number of wells used for the P-impedance inversion, the P-impedance is an attribute on the NN analysis, giving critical information to train the input data. We factored the P-impedance to have the P-wave for validation. The results show the comparison of the P-waves with the correlation of 79% in Fig. 7.

To further validate the porosity estimation, we have matched the predicted values with the well-log values for the three wells, CRC-1, CRC-2, and Naylor-1 achieving 88% of correlation in Fig. 8. The range of the porosity values was from 10 to 30%, notably higher at the CRC-2 than at the Naylor-1. Figure 9 depicts a cross-plot between the actual and predicted porosity. The PNN result demonstrated a range of porosity in the Paaratte formation of the Otway site favorable for CO2 disposal.

3.2 Porosity distribution of CO2 injection domain

Lebedev et al. (2013) conducted an experimental study of acoustic responses on the injection of Supercritical CO2 into sandstones from the Otway basin. They anticipated porosity distribution in this study area in the range between 14 and 25%. The result of the PNN assigned a porosity value at every grid point over the target domain. The PNN revealed the subtle diversity of porosity hard to notice on the seismic section alone. The time slice map at the 10 ms centered top of the Paaratte formation displayed a horizontal variation of computed porosity (Fig. 10a). The high porosity area covers from the northwest to center of monitoring domain indicated by light red color, where is the region of seismic difference is reported in recent publication (Fig. 10b; Popik et al. 2020). The amplitude difference in Fig. 10b represents of CO2 plume from first monitoring survey. In general, the porosity distribution obtained from the P-impedance inversion is evaluated with stratigraphy to avoid extreme regions. An iso-surface volume of 25% porosity showed the spatial extension from the injection well to the monitoring well in Fig. 11. The PNN result of the Paaratte formation could be substantial input for dynamic simulation of the Otway CO2 monitoring.

4 Discussion

Previous studies have calculated accurate porosity as a reservoir parameter from the well logs typically
The PNN was employed on the conventional reservoir to clarify the non-linear relation between geophysical attributes (Leiphart and Hart 2001). We calculated the porosity distribution in the Paaratte formation and provided the input for dynamic simulation. The result confirmed that the PNN is capable of creating the porosity distribution for monitoring the CO$_2$ in aquifer conditions. The computed porosity distribution of the Paaratte formation compares very well with the well logs over the entire depth range. Consistently over the whole domain, the equivalent resolution can be obtained with the PNN.

The horizontal disposition of the area with high porosity on the slice map (Fig. 10) corresponds with the previous time-lapse difference of the seismic amplitude (Urosevic et al. 2010; Popik et al. 2020). To accomplish complete CO$_2$ simulation in the Paaratte formation, we had to address permeability information as another property. The PNN also can develop permeability distributions from the geophysical data with anisotropic information. The Otway seismic research has been upgrading the result to achieve a quantitative level of CO$_2$ storage monitoring for aquifers (Pevzner et al. 2017b). Therefore, the proposed method helps to compute

![Graph](image-url)
**Fig. 9** Cross-plot of the actual porosity from the well log against the predicted porosity from the PNN method.

![Cross-plot of actual porosity against predicted porosity](image)

**Fig. 10** A time slice map of 
(a) the PNN porosity inversion results at the 10 ms centered depth of the Paaratte formation, 
(b) RMS amplitude of time-lapse signal difference between baseline and M1 survey data (Popik et al. 2020)

![Time slice maps](image)
reservoir parameters to enhance the CO₂ plume simulation continually.

5 Conclusions

Geomechanical simulation can demonstrate and anticipate change of subsurface properties to confirm CO₂ stabilization with time-lapse scale. In this paper, we estimated a porosity distribution of the saline aquifer in the Paaratte formation using the PNN. The estimated porosity can be used as input parameter for dynamic simulation. The proposed method of the neural network was conducted based on the integration of the well logs to the seismic volume, the inversion of acoustic impedance, and the inversion of porosity.

The cross-correlation between the actual and predicted porosity values exceeded 80% and well seismic correlation exceeded over 70% for all three wells. The time slice of the porosity distribution predicted that CO₂ storage expanded along with the highly porous media. The results of this study are summarized as follows: (1) The integrated framework of well log and seismic data for CCS research can be applied in the same way as for oil and gas exploration field; (2) By applying the PNN method, it is possible to correlate the well log and the seismic property; (3) As a result, porosity distribution was extended from a relatively small number of three well logs to the spatial region as dense as the lattice size of the geophysical data defines.

This study demonstrates that a geomechanical parameter estimated from geophysical data increases the overall confidence of the simulation for the aquifer of the Otway project. Integration between well log and seismic survey data would enhance certainty of geomechanical understanding on the CCS project. Further research on the permeability distribution, and other subsurface properties such as pressure or temperature with the PNN would complete the understanding of parameters for reservoir simulation.

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Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships.
that could have appeared to influence the work reported in this paper.

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