

PS Constructing a Geological Model to Estimate the Capacity of Commercial Scale Injection, Utilization and Storage of CO₂ in the Jacksonburg-Stringtown Field, West Virginia, USA*

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Abstract

Geological capture, utilization, and storage (CCUS) of carbon dioxide (CO₂) in depleted oil and gas reservoirs is one method to reduce greenhouse gas emissions while enhancing oil recovery (EOR) and extending the life of the field. Therefore CCUS coupled with EOR is considered to be an economic approach to demonstration of commercial-scale injection and storage of anthropogenic CO₂. Several critical issues should be taken into account prior to injecting large volumes of CO₂, such as storage capacity, project duration, and long-term containment. The storage capacity of CO₂ is estimated by methods used by the petroleum industry in the characterization of hydrocarbon accumulations. The Jacksonburg-Stringtown Field, located in northwestern West Virginia, has produced over 22 million barrels of oil (MMBO) since 1895. The sandstone of the Late Devonian Gordon Stray is the primary reservoir. Well log analysis is used to define four reservoir subunits within a marine-dominated estuarine depositional system: barrier sand, central bay shale, tidal channels, and fluvial channel subunits. A 3D geologic model was constructed with variable-quality data from 175 wells to estimate the storage capacity and optimize simulation strategies to evaluate commercially-viable geological storage and EOR. Artificial neural network (ANN) of petrophysical log data (Vsh, slope of GR, ILD, slope of ILD, and DPHI) were utilized as inputs and target outputs to train neural network to characterize reservoir units. The ANN is a powerful tool to develop maps of critical reservoir parameters and focused simulation. The best regions for CCUS-EOR are located in southern regions of the field. Estimated theoretical CO₂ storage is approximately 24 million metric tons.

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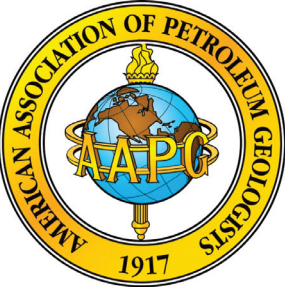
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Abstract

Geological capture, utilization and storage (CCUS) of carbon dioxide (CO₂) in depleted oil and gas reservoirs is one method to reduce greenhouse gas emissions while enhancing oil recovery (EOR) and extending the life of the field. Therefore CCUS coupled with EOR is considered to be an economic approach to demonstration of commercial-scale injection and storage of anthropogenic CO₂. Several critical issues should be taken into account prior to injecting large volumes of CO₂, such as storage capacity, project duration and long-term containment. The storage capacity of CO₂ is estimated by methods used by the petroleum industry in the characterization of hydrocarbon accumulations.

The Jacksonburg-Stringtown field, located in northwestern West Virginia, has produced over 22 million barrels of oil (MMBO) since 1895. The sandstone of the Late Devonian Gordon Stray is the primary reservoir. Well log analysis is used to define four reservoir subunits within a marine-dominated estuarine depositional system: barrier sand, central bay shale, tidal channels and fluvial channel subunits. A 3D geologic model was constructed with variable-quality data from 175 wells to estimate the storage capacity and optimize simulation strategies to evaluate commercially-viable geological storage and EOR. Artificial neural network (ANN) of petrophysical log data (GR, slope of GR, density, slope of density, and V_{sh}) were utilized as inputs and target output to train neural network to characterize reservoir units. The ANN is a powerful tool to develop maps of critical reservoir parameters and focused simulation. The best regions for CCUS-EOR are located in southern regions of the field. Estimated theoretical CO₂ storage is approximately 24 million metric tons.

Objective

The Gordon Stray formation is a high quality hydrocarbon producing reservoir and represents an encouraging future target for CO₂ storage operations. This study was an attempt to better define the depositional framework and reservoir characteristics of the Gordon Stray formation within the Jacksonburg-Stringtown field in northern West Virginia. These objectives were achieved with the aid of well log data, online hydrocarbon production archives, and sample reservoir hydrocarbon analysis.

Geologic Background

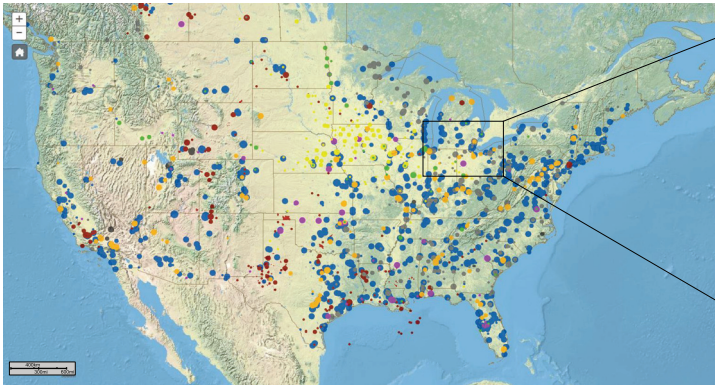


Fig. 1 Oil fields with a minimum of one million barrels of documented oil production and large CO₂ stationary sources (metric tons) in the Appalachian basin.

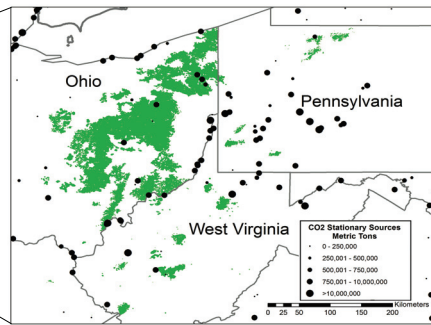


Fig. 2 Location of the Jacksonburg-Stringtown field is highlighted (Data from the US DOE Carbon Storage and Utilization Atlas).

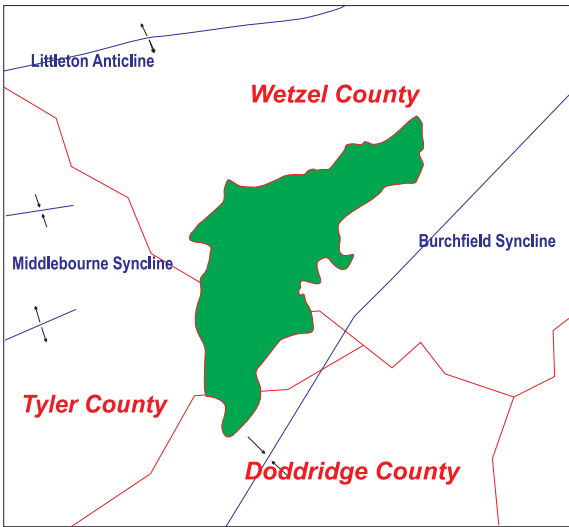


Fig. 3 Map of the study area including the location of the Jacksonburg-Stringtown oil field in northwestern West Virginia

The Jacksonburg-Stringtown field located in northwestern West Virginia is a well-known oil and gas producer. This field sits along the western edge of the Burchfield syncline (Fig. 3).

Since discovered in 1895, this field has produced over 22 million barrels of oil (MMBO). The average well space is 13 acres. In 1981, this field started a waterflood program with a pilot utilizing a 35-acre dual 5-spot pattern. After 1990, full-scale water flood operations began. CO₂ flood plays an important role in the outcome of a waterflood.

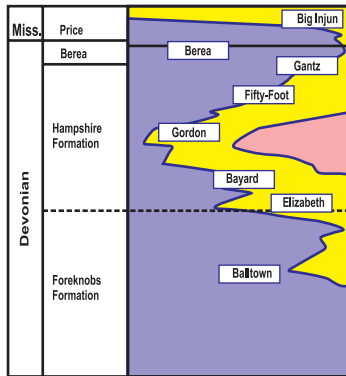


Fig. 4 Generalized stratigraphic column for the Late Devonian of the Appalachian basin showing subsurface (right) and outcrop (left) terminology. Shading indicates relative shifts in paleocoastline locations (After Ameri et al., 2002).

Available Data

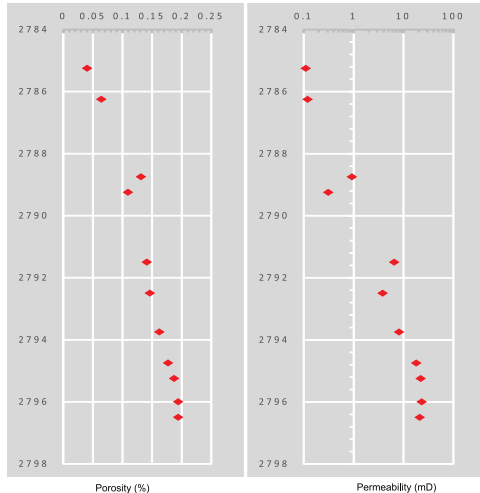


Fig. 5 Measured Core Porosity and Permeability (Well API: 4709501125)

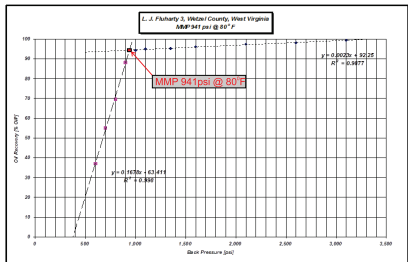


Fig. 8 Minimum miscibility pressure (MMP) plot using a sample of oil from the Jacksonburg-Stringtown field at a reservoir temperature of 80 °F. Oil density is 0.7954 g/cc (46.5 deg. API). Solvent (miscible) with in-situ oil above 941 psi.

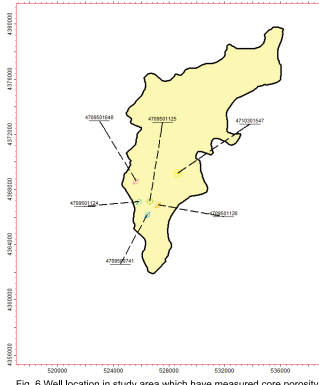


Fig. 6 Well location in study area which have measured core porosity and permeability

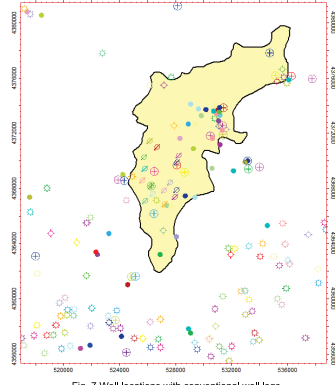


Fig. 7 Well locations with conventional well logs

Tab. 1 Summary of Jacksonburg-Stringtown research cores

Well	Cored Interval, ft	Avg. Porosity %	Avg. Permeability md
B-18	2988.5-3014	14.7	52
B-19	3086-3115	14.9	41
H-9	2980-2908	18.2	106
H-11	3083.4-3093.4	18.8	72
T-8	2781-2797	12.4	6.5
L-13	3032.4-3061.5	8.4	2.5

Totally, 93 samples with both core data and conventional logs were collected from 6 wells in the Jacksonburg-Stringtown field (Fig. 6) as training data to build up a regression model to predict porosity values.

Estuarine Model

Depositional facies and external geometry determine the reservoir quality. Properly identifying and characterizing the depositional framework is critical in determining the quality of a hydrocarbon reservoir. Estuarine depositional systems occur within drowned incised valleys during an overall transgressive period, where sea level rise overtakes sediment supply from marine and terrestrial sources. There are two subtypes of estuarine systems: wave-dominated and tide-dominated estuaries (Fig. 9).

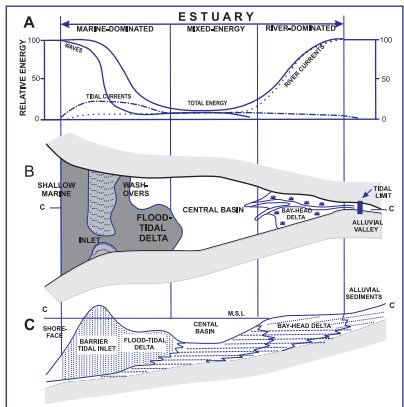
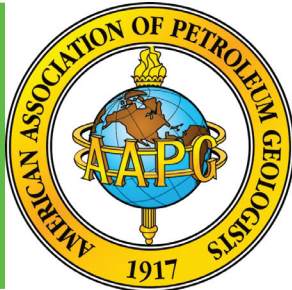


Fig. 9 Idealized wave-dominated estuarine system model showing depositional facies and changes in relative energy (After Dalrymple et al., 1992)



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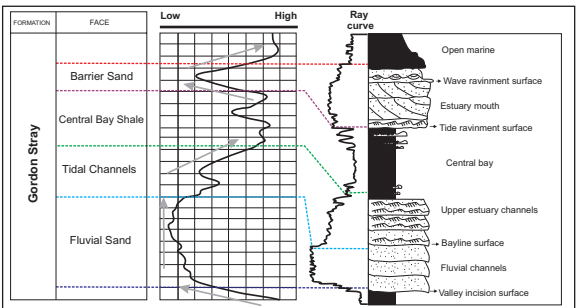


Fig. 10 Comparison of example Gordon Stray interval gamma log signature from the Jacksonburg-Stringtown field with idealized model. (API#4710300595)

The signature of the Gordon Stray intervals relatively follows an idealized estuarine vertical succession by examining the logs from the Jacksonburg-Stringtown field (Fig. 10). The thinner upper sand is interpreted as the estuary mouth deposit, meanwhile the much thicker lower sand can be identified as tidal dominated deltaic deposits, and inner interval is estuarine shale. The lowest subunit is fluvial deposits.

Structure Model

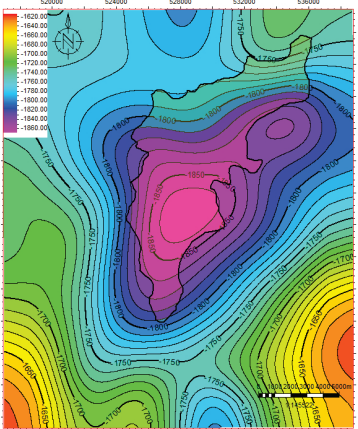
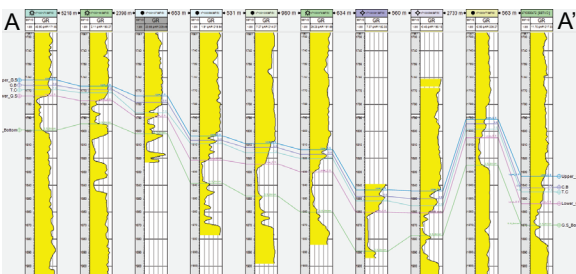


Fig. 11 Barrier Sand structure map, 10 ft contour intervals.

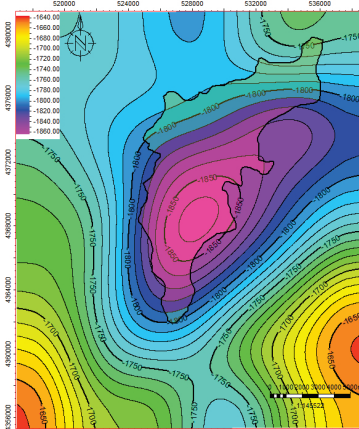


Fig. 12 Central bay shale structure map, 10 ft contour intervals.

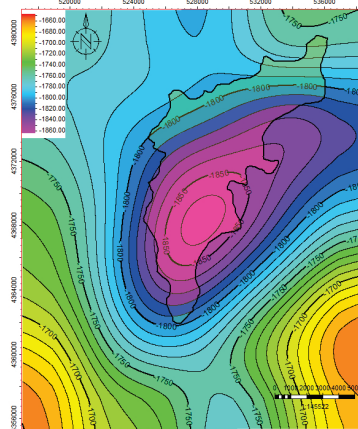


Fig. 13 Tidal Channel structure map, 10 ft contour intervals.

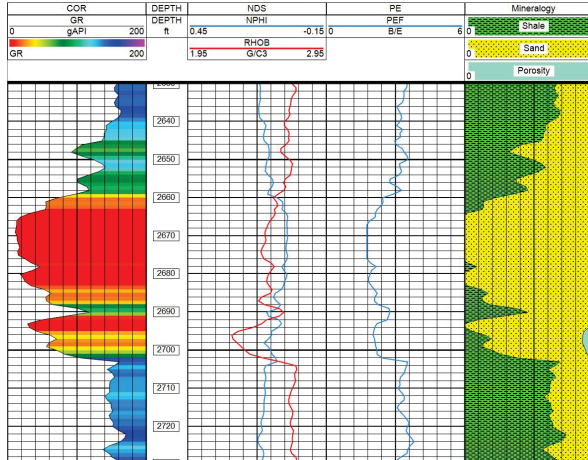


Fig. 19 Mineral Composition analysis of Gordon Stray intervals.

Mineral Composition of Gordon Stray intervals was established (Fig. 19). As Lower Gordon Stray shows, High quality of sandstone and more poro volume indicates that this intervals has high capacity of CO₂ storage. Estimated pressure at the top of the Lower Gordon Stray reservoir subunit meets the requirements for CO₂ supercritical state (1087 psi) and CO₂ miscibility (941 psi).

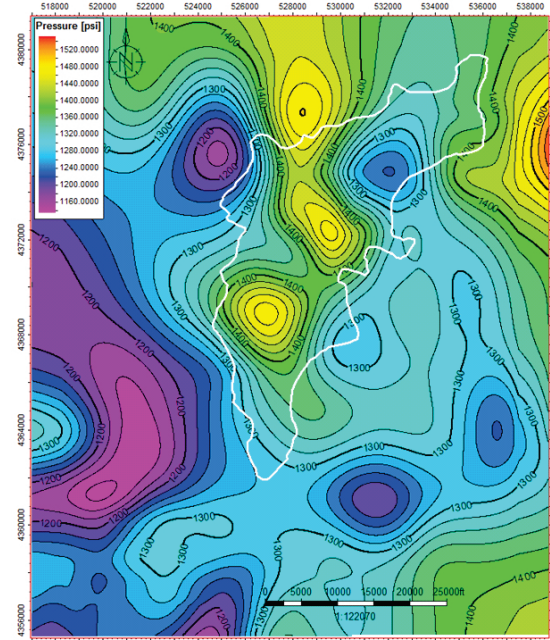


Fig. 20 Estimated pressure at the top of the Lower Gordon Stray reservoir subunit meets the requirements for CO₂ supercritical state (1087 psi) and CO₂ miscibility (941 psi).

Methodology

Mathematical perceptron first proposed by McCulloch, are prototype of neural networks which mimicked the biological neuron behavior. Héroult and Jutten describe the process of biological neuron transiting signals from one to others (a). Mathematical neuron (b) simplify the biological neuron's signal bypass process, and then weighted sum of inputs (c) can be rescaled by the activation function (d). Combination of a series of mathematical neurons constructed the artificial neural network (Fig. 22).

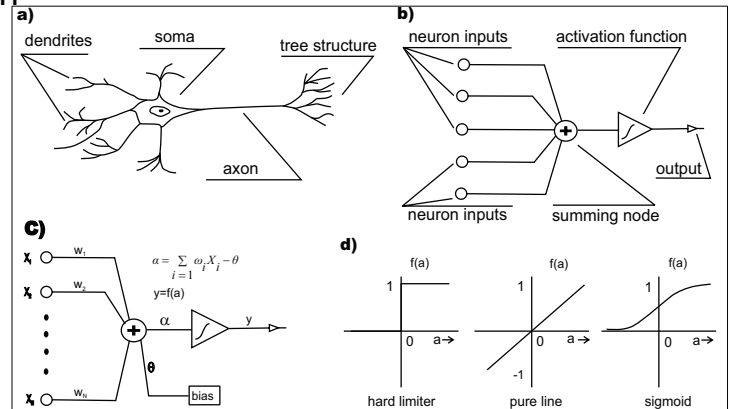


Fig. 21 Mathematical perceptron are prototype of neural networks which mimicked the biological neuron behavior.

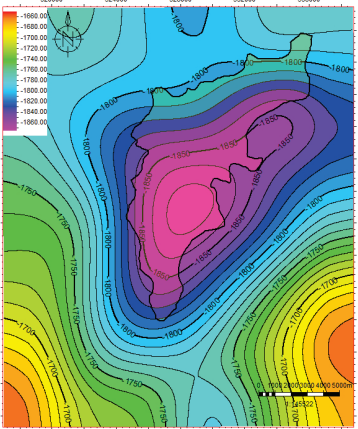
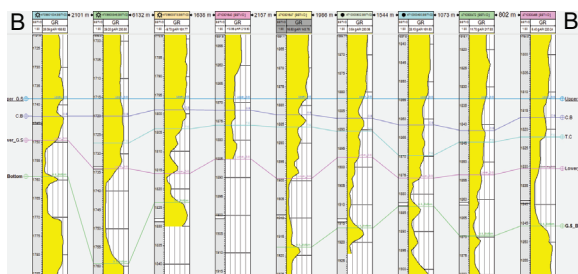
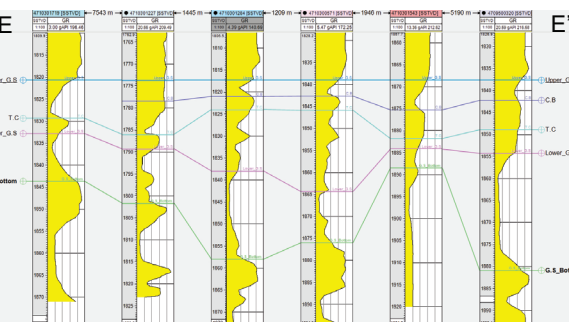
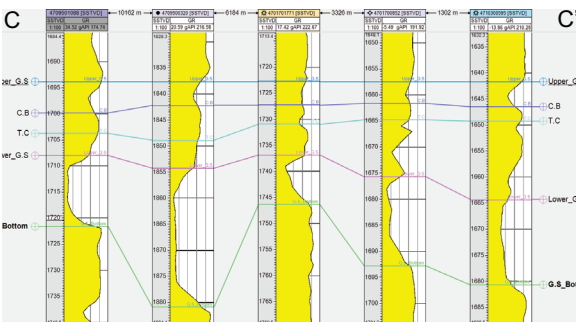


Fig. 14 Lower Gordon stray structure map, 10 ft contour intervals.

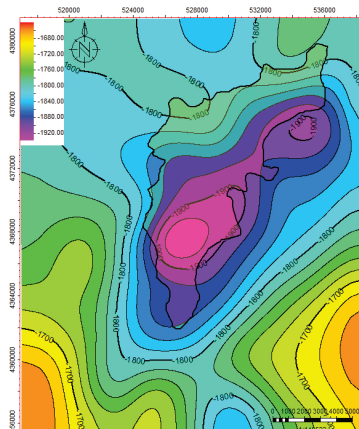


Fig. 15 Lower Gordon stray bottom structure map, 20 ft contour intervals.

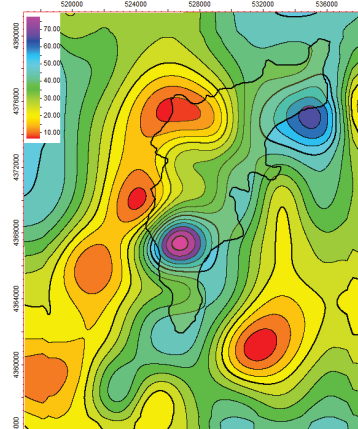


Fig. 16 Gordon Stray isopach map. Thickest parts are more than 70 ft (10 ft contour intervals).

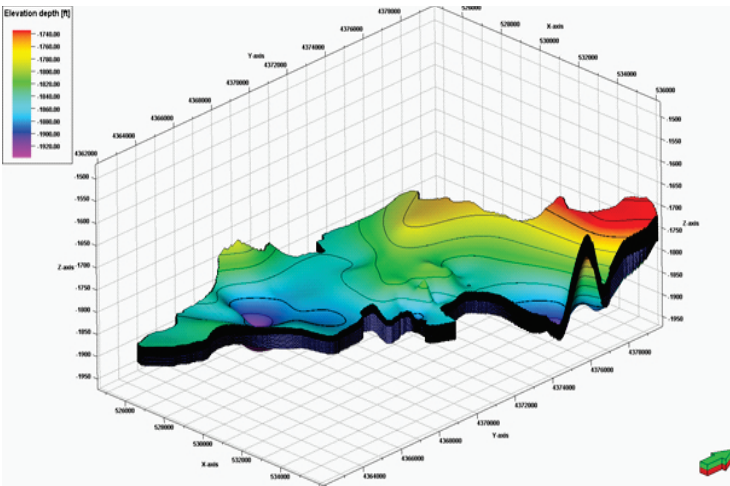


Fig. 17 3-D static geologic model of Gordon Stray interval in Jacksonburg-Stringtown

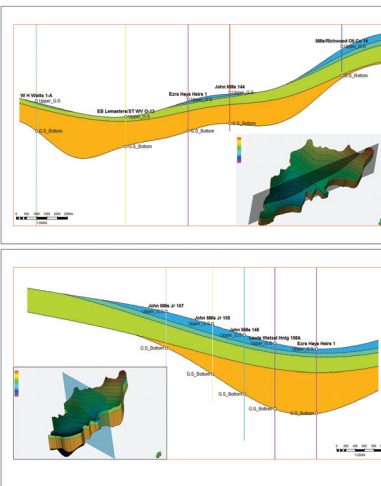
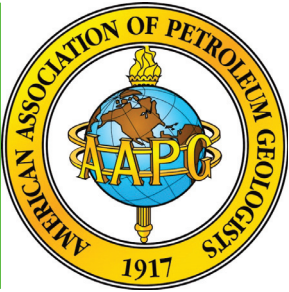


Fig. 18 Crosssection of structure model



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Artificial neural networks can learn anything it wants to express, and provides a nonlinear mapping between inputs and outputs by their intrinsic ability. However, the process of minimizing convergence rate to zero during network training can cause overtraining, also known as overfit, due to memorization of the training set.

Principal component analysis also was applied to optimize ANN structure and reduce overfitting effect. Here, two evolutionary algorithms: Genetic algorithm (GA) and particle swarm optimizatoin (PSO) are applied to optimizing the weights and biases for each single node in back-propagation neural network (BP-NN), and to minimizing the effect of overfitting. In order to evaluate the performance of BPNN training and testing process, the mean squared error (MSE) of the network is defined as follows:

$$MSE = \frac{1}{m} \sum_{j=1}^m [Y_j(k) - T_j(k)]^2$$

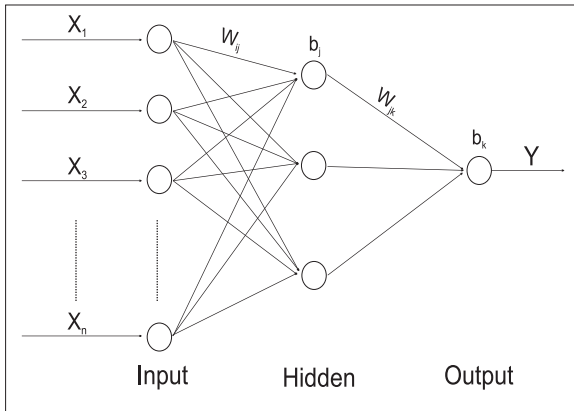


Fig.22 BP neural network topology

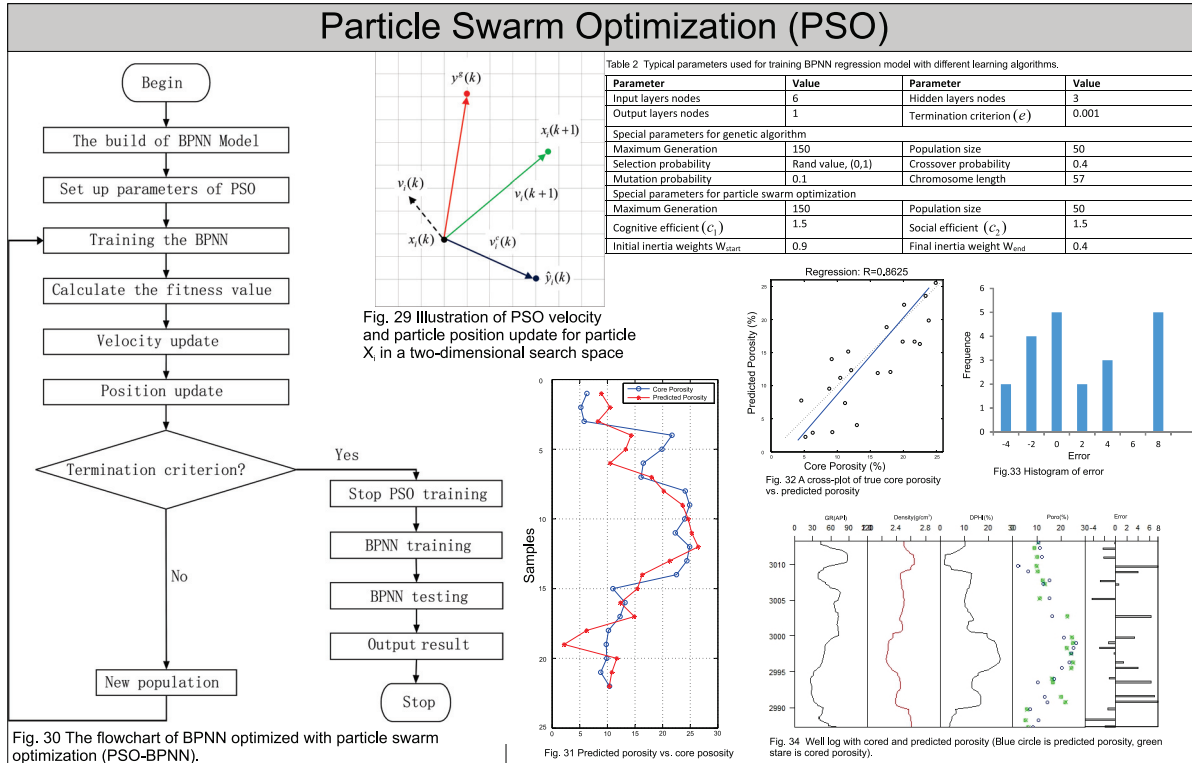


Fig. 30 The flowchart of BPNN optimized with particle swarm optimization (PSO-BPNN).

Particle Swarm Optimization (PSO)

Table 2 Typical parameters used for training BPNN regression model with different learning algorithms.

Parameter	Value	Parameter	Value
Input layers nodes	6	Hidden layers nodes	3
Output layers nodes	1	Termination criterion (ϵ)	0.001
Special parameters for genetic algorithm			
Maximum Generation	150	Population size	50
Random value, (0,1)		Crossover probability	0.4
Mutation probability	0.1	Chromosome length	57
Special parameters for particle swarm optimization			
Maximum Generation	150	Population size	50
Cognitive efficient (c_1)	1.5	Social efficient (c_2)	1.5
Initial inertia weights W_{start}	0.9	Final inertia weight W_{end}	0.4

Fig. 29 Illustration of PSO velocity and particle position update for particle X_i in a two-dimensional search space

Fig. 32 A cross-plot of true core porosity vs. predicted porosity

Fig. 33 Histogram of error

Fig. 34 Well log with cored and predicted porosity (Blue circle is predicted porosity, green star is cored porosity).

Fig. 35 Major direction variogram

Fig. 36 Major direction variogram

Fig. 37 porosity model with Sequential Gaussian Simulation

Fig. 38 porosity model with Gaussian Random Function Simulation

Fig. 39 porosity model with Gaussian Random Function Simulation

Fig. 40 porosity model with Gaussian Random Function Simulation

Fig. 41 porosity model with Gaussian Random Function Simulation

Fig. 42 porosity model with Gaussian Random Function Simulation

Fig. 43 porosity model with Gaussian Random Function Simulation

Fig. 44 porosity model with Gaussian Random Function Simulation

Fig. 45 porosity model with Gaussian Random Function Simulation

Fig. 46 porosity model with Gaussian Random Function Simulation

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Fig. 49 porosity model with Gaussian Random Function Simulation

Fig. 50 porosity model with Gaussian Random Function Simulation

Fig. 51 porosity model with Gaussian Random Function Simulation

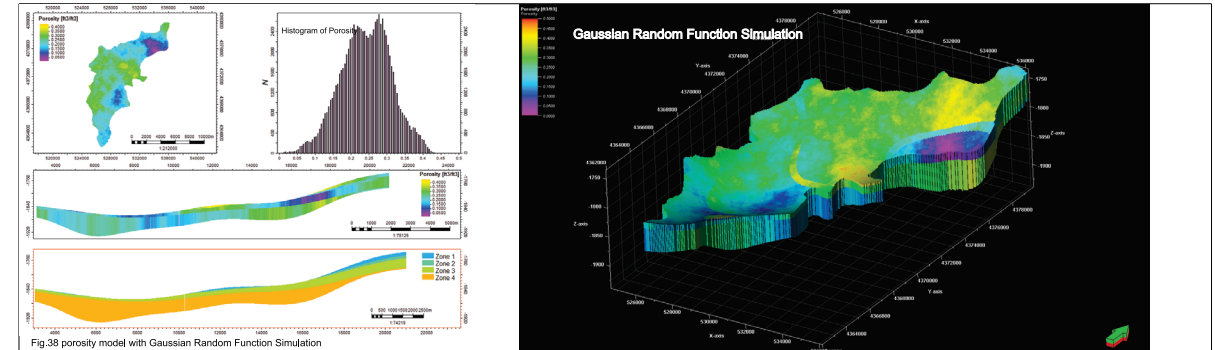
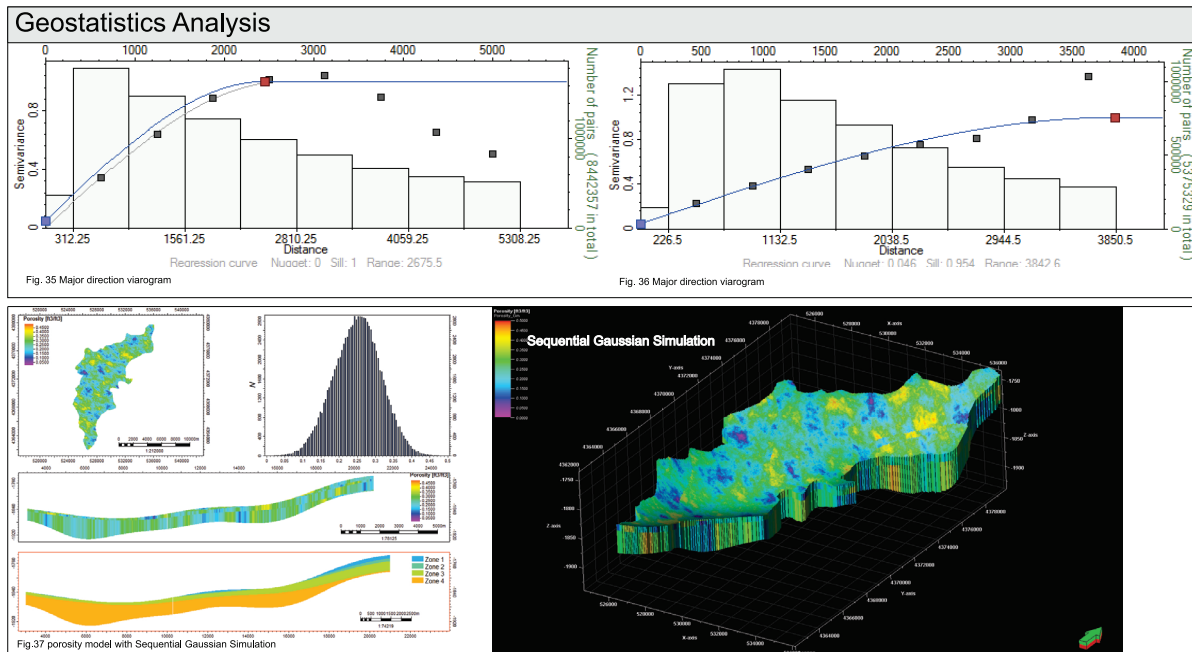
Fig. 52 porosity model with Gaussian Random Function Simulation

Fig. 53 porosity model with Gaussian Random Function Simulation

Fig. 54 porosity model with Gaussian Random Function Simulation

Fig. 55 porosity model with Gaussian Random Function Simulation

Petrophysical Model- Porosity Model



Result

$$M_{CO_2} = A \cdot H_n \cdot \phi_e \cdot (1 - S_{wi}) \cdot B \cdot \rho_{CO_2} \cdot E$$

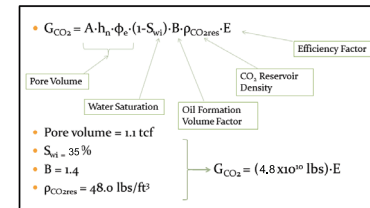


Table 3. Storage efficiency factors and Resulting storage resource for the P_{10} , P_{50} and P_{90} in Jacksonburg-Stringtown.

Volume Statistics					
Parameter	Symbol	Unit	P_{10}	P_{50}	P_{90}
Total Pore Volume (ft ³)	V_{pv}	tft ³	1.1	1.3	1.408
Water Saturation	S_{wi}	%	0.35	0.25	0.1
Formation Volume Factor	B	Bbl/STB	1.4	1.4	1.4
Average CO2 Density Max	ρ_{co2}	lbs/ft ³	48.0	48.0	48.0
Efficiency Factor	E	%	0.1	0.5	0.9
Reservoir CO ₂ Storage Mass	M_{co2}	Mt	24.0	163.8	383.2

Summary

1. GR, slop of GR, density, slop of density, and V_{sh} can be utilized as inputs and porosity can be utilized as output to build up the Back-Propagation Neural Network (BPNN).
2. Artificial neural network performance very well to predict the the porosity value with high correlation coefficient.
3. Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) were used to optimize BPNN structure. GA performance better than PSO.
4. Most confidence storage capacity is 24 million tons, and most risk storage capacity is 383 Mt.
5. In future, CO₂-EOR numerical fluid-flow model should be constructed. Examining the economic feasibility.

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