Injection Pattern Design to Maximize the Efficiency of Carbon Dioxide Injection for Sequestration Purposes in Brine Formations*

Qian Sun[1] and Turgay Ertekin[2]

Search and Discovery Article #80334 (2013)
Posted October 31, 2013

*Adapted from extended abstract prepared in conjunction with poster presentation at AAPG Annual Convention and Exhibition, Pittsburgh, Pennsylvania, May 19-22, 2013, AAPG©2013

[1]The Penn State University, University Park, PA, United States (gradsunqian@gmail.com)
[2]The Penn State University, University Park, PA, United States

Abstract

In CO_2 deep saline sequestration projects, reservoir pressure build up is one of the main restrictions. Although the application of horizontal injection well would improve the injectivity, it could not increase the capacity of the reservoir unless there is an external mechanism to dissipate pressure. The effect of pressure build up would be especially important when multiple injection wells are used. One of the feasible methods to decrease the reservoir pressure is to extract the brine in the formation to create more available volume for CO_2 injection. The target formation of this study is the Mt. Simon Sandstone Formation. The large nature of the reservoir and variation of key storage and transport characteristics of the Mt. Simon Sandstone Formation are also two of the challenges of this study. Besides, as brine production is used to reduce the injection pressure limitation, CO_2 breakthrough may happen at the production well prematurely, which potentially can reduce the efficacy of the CO_2 injection operation. More importantly, the post injection stabilized reservoir pressure should be another important concern. The post injection stabilized reservoir pressure should be maintained below a safety level to prevent the injected CO_2 from migrating upwards through the formation seal.

Previous studies done by Sun and Ertekin (2012) show that the regular 4-spot injection pattern has the best injection performance when comparing with other types of injection patterns. The objective of this work is to study the relationship between the CO_2 injectivity and the design parameters of CO_2 injection patterns and to generate a solution to obtain the optimal design of the injection pattern. A commercial numerical simulator, the compositional numerical simulator in Computer Modeling Group software suit (CMG-GEM) is employed as the numerical tool for the simulation. This work implements Monte Carlo Simulation protocol for multiple simulation runs with different combinations of reservoir properties to reduce the uncertainties from the nature of the formation. This work also runs multiple simulations with different combinations of design parameters to generate one-to-one relationships between the pattern design parameters and the projects output. Then the optimal design of injection pattern can be determined.

The commercial simulator is a high-fidelity model. If these Monte Carlo runs totally rely on hard computation, the simulation will take considerable time and be hard drive space consuming. In order to address these issues, this study employed artificial neural network as a soft computation technique. If an expert system for this problem can be trained, it can predict the output accurately within a fraction of a second. More importantly, the expert system helps to generate large amount of Monte Carlo simulation runs with in short period of time.

The regular 4-spot injection pattern is modeled in a 30×30×1 grid system, as shown in Figure 1. Table 1 shows the ranges of reservoir properties and injection pattern parameters. One thousand groups of input data within corresponding ranges are generated and combined randomly. One can run simulation using the commercial software with those 1,000 groups of input data and 1,000 groups of output data will be generated. Two different expert systems are developed for different simulation purposes:

1. End-point forward-looking solution network (EFSN), with input of reservoir properties and engineering design parameters and output of cumulative CO_2 injection, injection efficiency, and pressure depletion ratio at the end of the injection period. The architecture design of EFSN is shown in Figure 2.

2. Injection efficiency profile network (IEPN), with input of reservoir properties and engineering design parameters and output of injection efficiency profile at different times. The architecture design of IEPN is shown in Figure 3.

These two artificial neural networks are validated through internal blind tests. These tests show error margins of around 10%, which indicates that the expert systems are well trained and can be used to predict simulation results. Figure 4, Figure 5, Figure 6, and Figure 7 show the tests result of these expert systems.

By implementing the EFSN, one can generate simulation runs by large number of different combinations of design parameters to determine the optimal design. The Mt. Simon Formation in the Michigan Basin is selected as the field cases. The regression equation developed by Medina et al. (2010) describing the permeability and porosity of the reservoir as a function of burial depth is employed to generate the permeability and porosity distribution maps. Then the cumulative CO_2 injection distribution map can be generated (Figure 8). The IEPN helps to generate the injection efficiency distribution maps at different times (Figure 9).

References Cited

Medina, C. et al., 2012, A regional characterization and assessment of geologic carbon sequestration opportunities in the upper Cambrian Mount Simon sandstone in the Midwest region: MRCSP Phase II Topical Report.

Sun, Q, and T. Ertekin, 2012, Design of Multiple Brine Producer/Injector Configurations to Increase Carbon Dioxide Injectivity in Saline Formations: AIChE.

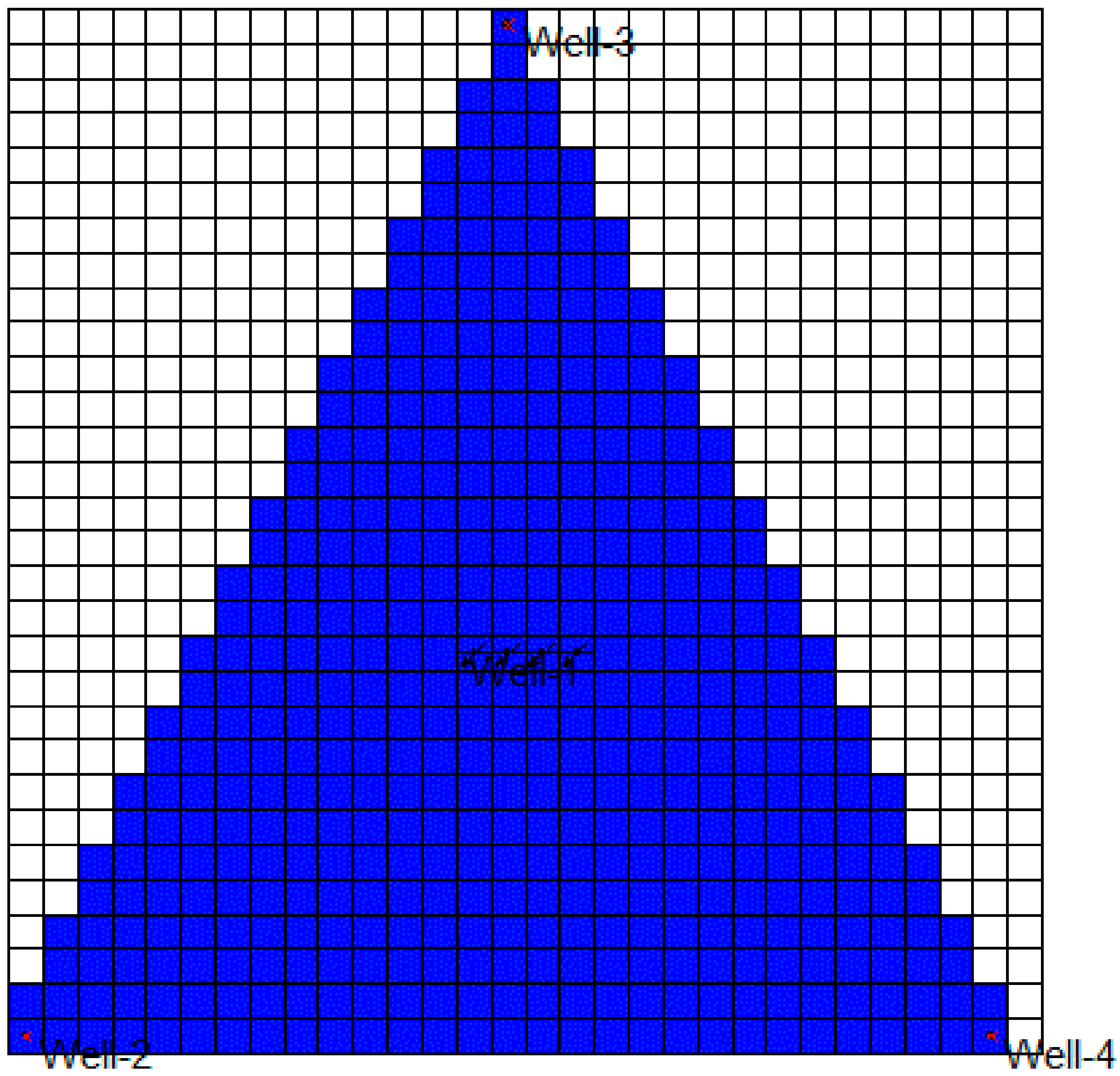


Figure 1. 2-D simulation model for 4-spot injection pattern.

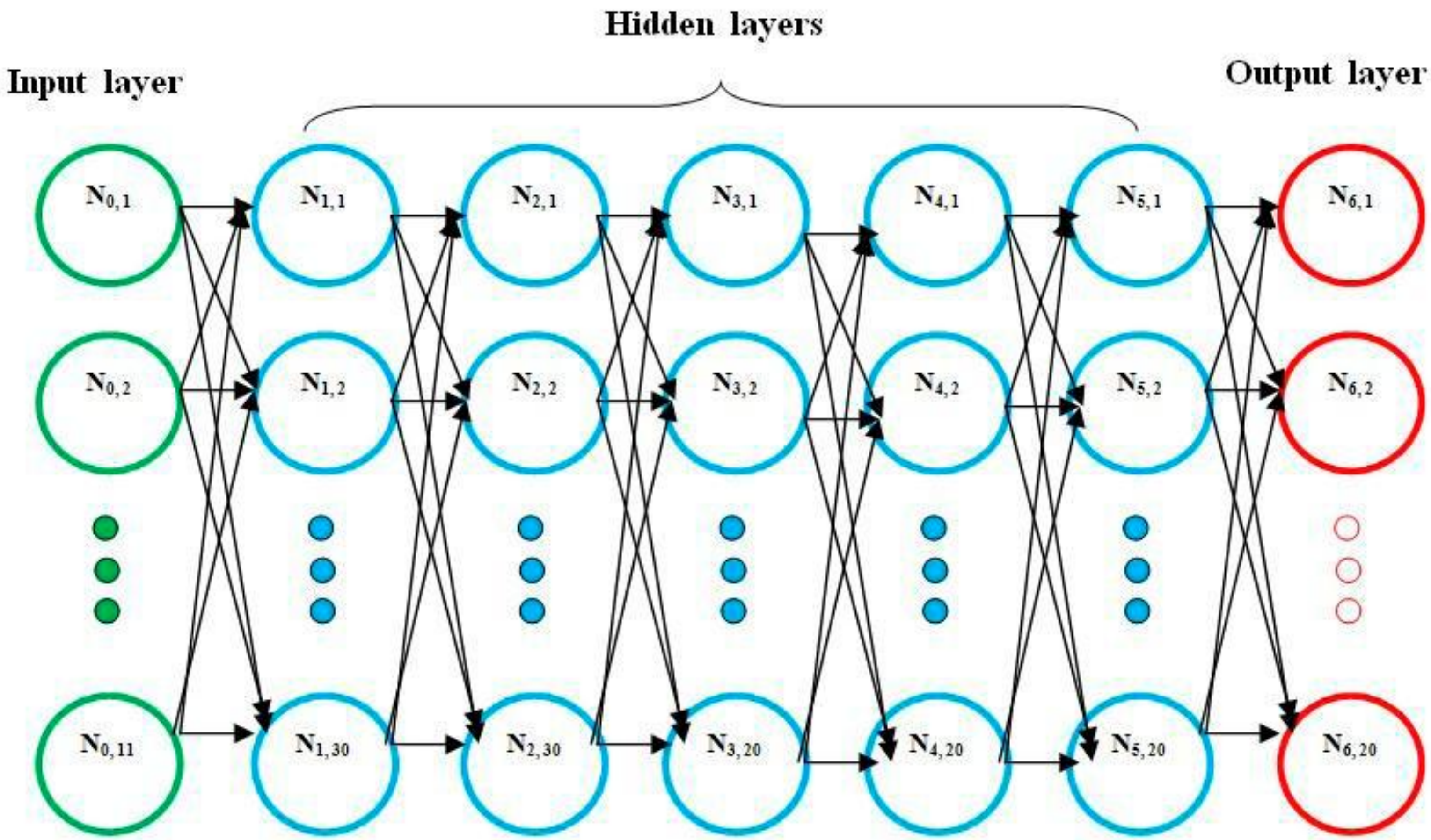


Figure 2. Architecture of EFSN.

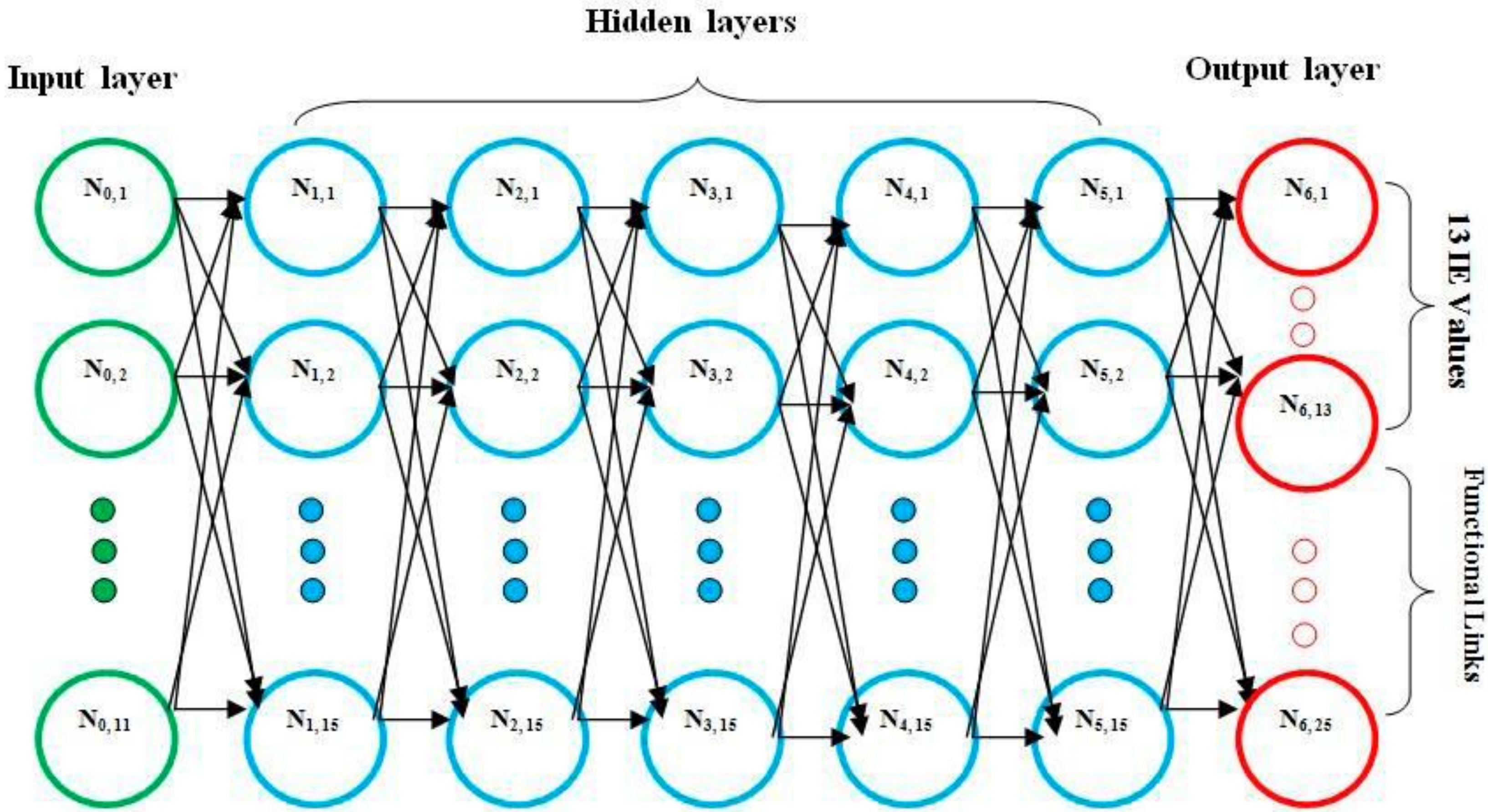


Figure 3. Architecture of IEPN.

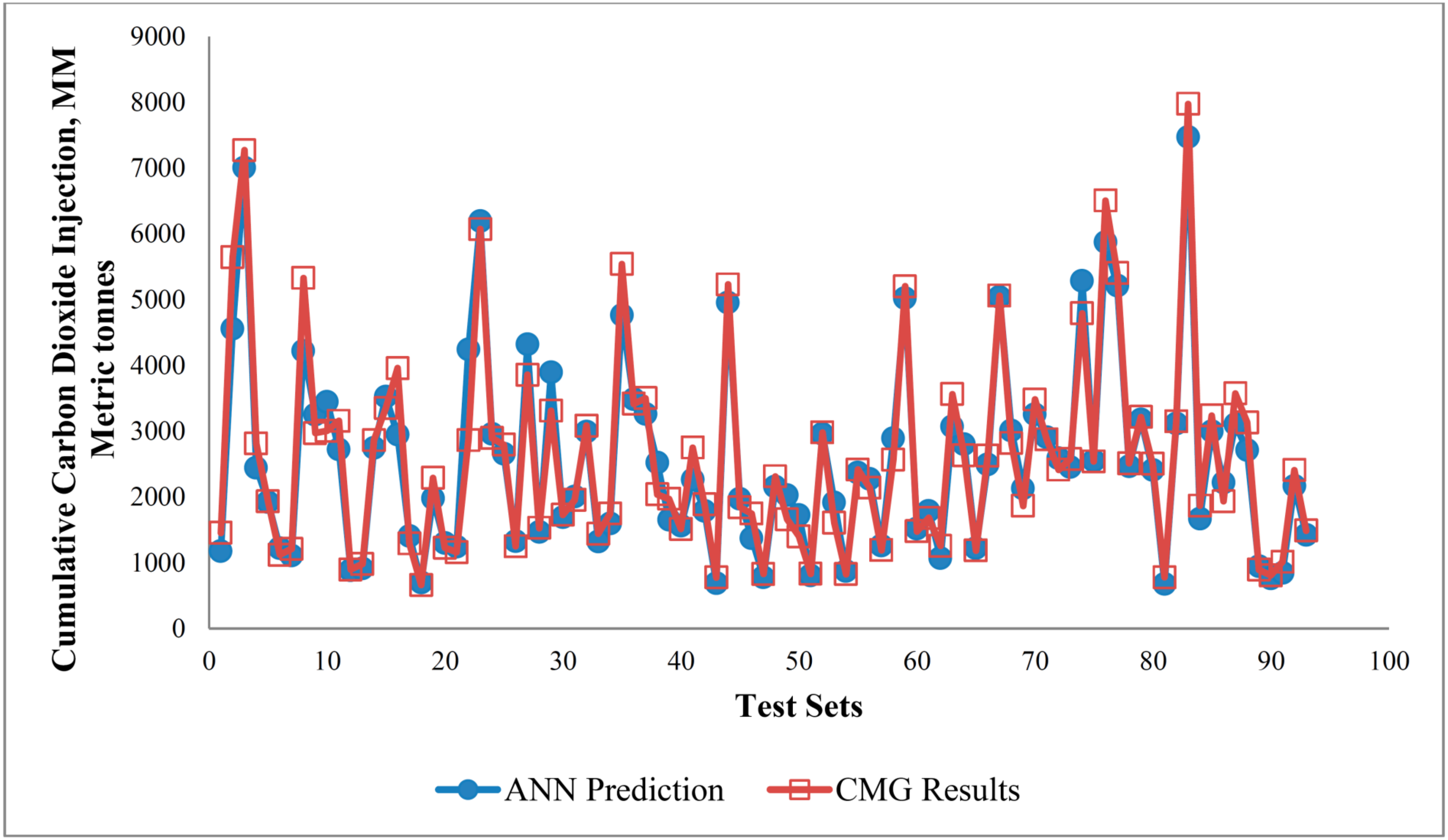


Figure 4. Comparison of EFSN prediction and numerical model results of cumulative CO_2 injection.

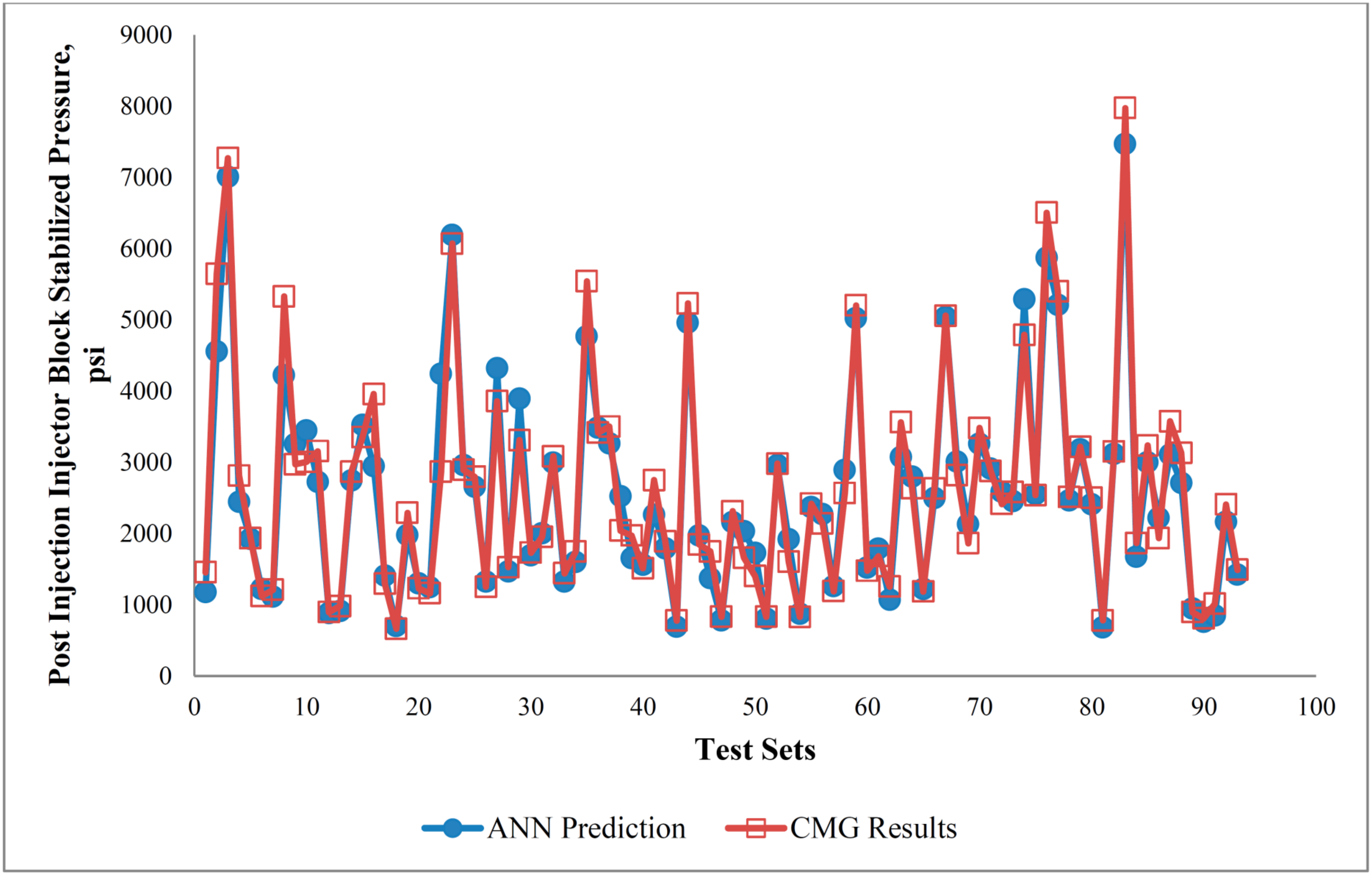


Figure 5. Comparison of EFSN prediction and numerical model results of stabilized injector block pressure.

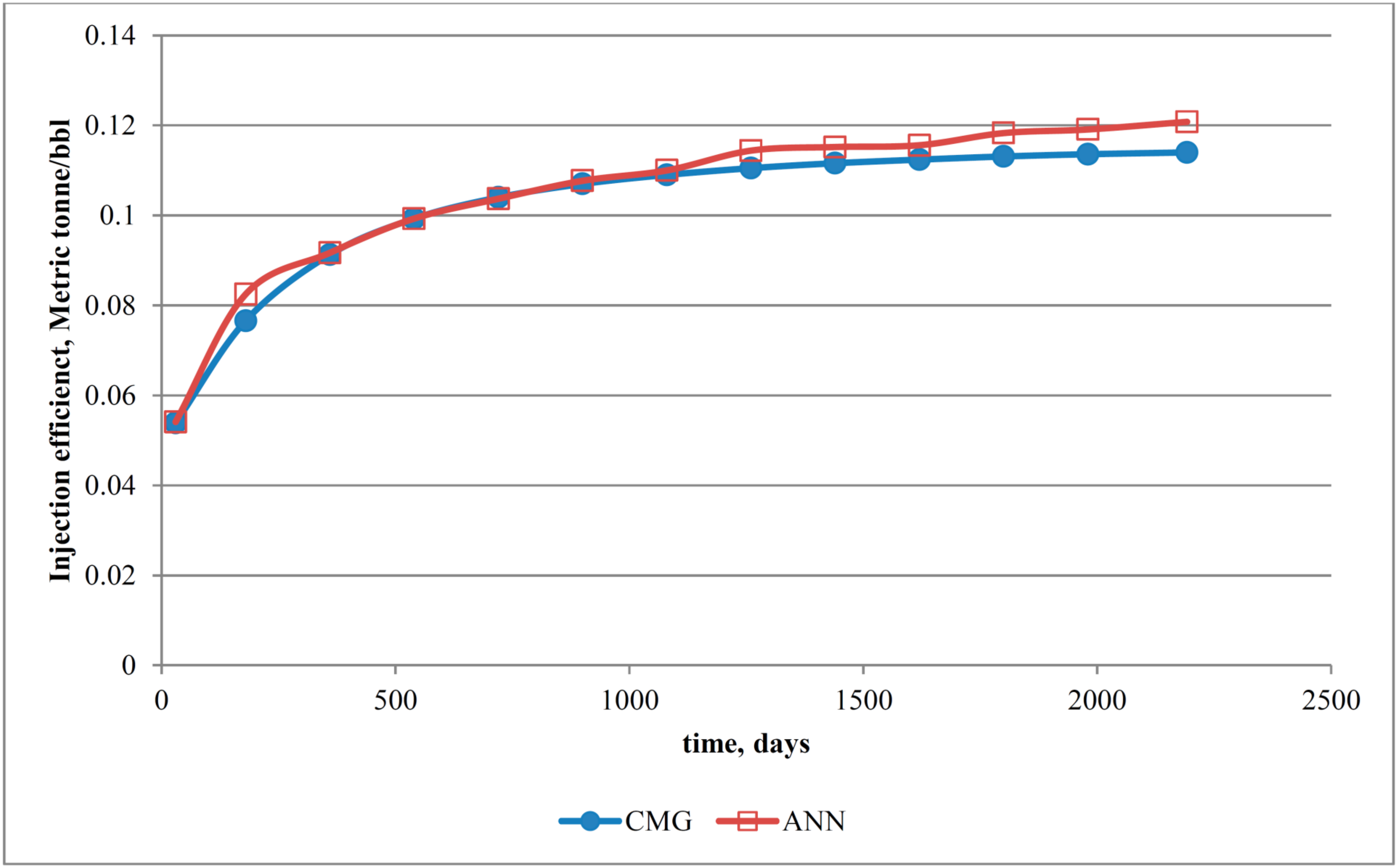


Figure 6. Injection efficiency profiles predicted by IEPN and numerical model, Case 1.

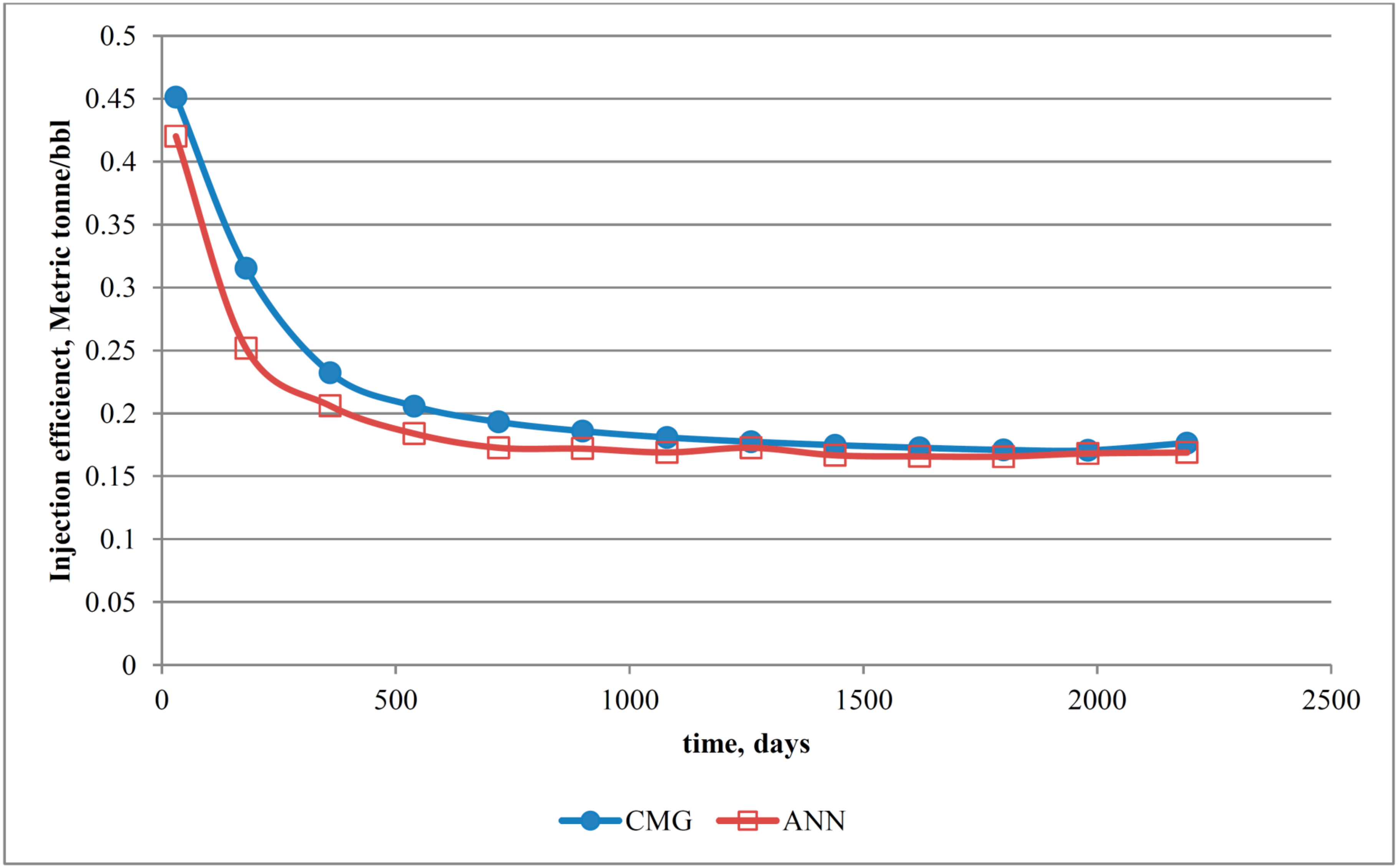


Figure 7. Injection efficiency profiles predicted by IEPN and numerical model, Case 2.

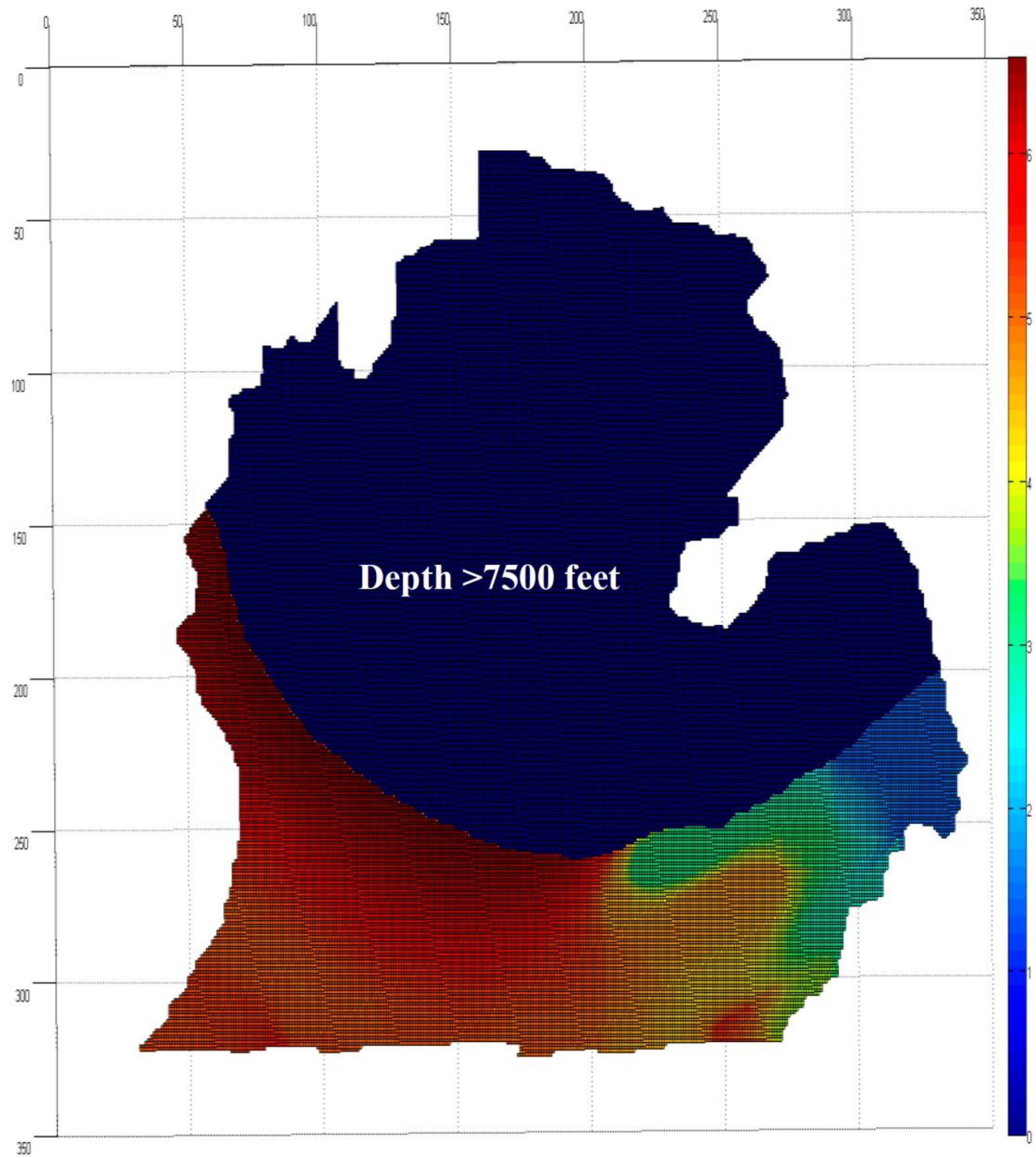
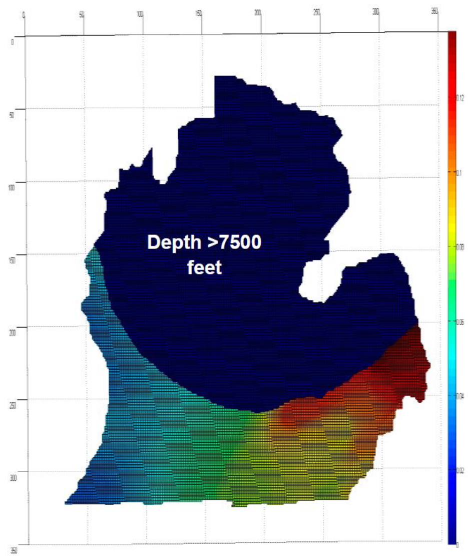
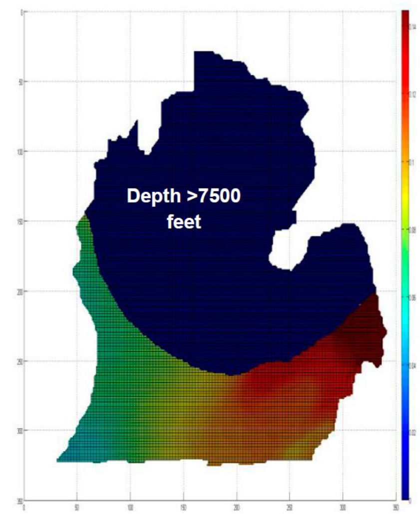


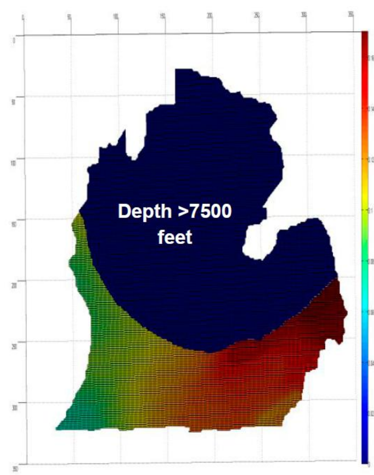
Figure 8. Cumulative CO_2 injection distribution map in Michigan Basin.



Injection efficiency distribution map in Michigan Basin at the end of 2012



Injection efficiency distribution map in Michigan Basin at the end of 2014



Injection efficiency distribution map in Michigan Basin at the end of 2017

Figure 9. Injection efficiency distribution at the end of 2012, 2014, and 2017.

Reservoir Property and Design Parameter Reservoir Property and Design Parameter		Training Data Range
Reservoir properties	k(md)	0.5-150
	h(ft)	50-2600
	Ø,(fraction)	0.01-0.25
	D(feet)	2000-8500
	$\frac{\partial P_i}{\partial Z}$ (psi/ft)	0.433-0.5
	$\frac{\partial T_i}{\partial Z}$ (ºF/1,000 ft)	9.5-12
	$\frac{\partial P_{frac}}{\partial Z}$ (psi/ft)	0.6-0.9
Design parameters	A(acres)	70-640
	Q (MMSCFD)	1-250
	L_w (feet)	500-1500
	P_{wf}, fraction of P_i	0.5~0.95

Table 1. Summary of training data ranges.