Artificial Neural Network (ANN) Prediction of Porosity and Water Saturation of Shaly Sandstone Reservoirs*

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Abstract

This paper presents a successful application of neural networks (ANN) in predicting porosity, water saturation, and identifying lithofacies of shaly sand reservoir using well logging data. ANN technique utilizes the prevailing unknown nonlinear relationship in data between well logs and the reservoir rock petrophysical properties. In heterogeneous reservoirs classical methods face problems in determining accurately the relevant petrophysical parameters due to assumptions and uncertainties of input parameters. Applications of artificial intelligence have recently made this challenge a possible practice and in this study neural network has been proposed to supplement or replace the existing conventional techniques to determine water saturation using shaly water saturation models (total shale, Simandoux, and medium effective) and effective porosity in shaly sand reservoirs. Two neural networks were presented to determine porosity and water saturation using GR, resistivity and density logging data and the cut off values for porosity and water saturation. Water saturation and porosity have been determined using conventional techniques and neural network approach for two wells drilled in a shaly sand reservoir. ANN outputs have shown good matching with core data and the reference calculated petrophysical parameters; porosity, water saturation, and defined pay zones in a new well that projects its application for new wells. Neural network approached have trained for porosity and water saturation using the available well logging data. The predicted porosity and water saturation values have shown excellent matching with core data in the two wells compared to the porosity and water saturation of the conventional techniques. Consequently, the developed network (ANN) can successfully deduce porosity, water saturation, and defined pay zones of for new wells in shaly sand.

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Artificial Neural Network (ANN) Prediction of Porosity and Water Saturation of Shaly Sandstone Reservoirs

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Outline

- INTRODUCTION
- LITERATURE REVIEW
- METHODOLOGY
- RESULTS AND DISCUSSION
- CONCLUSION AND RECOMMENDATION
- REFERENCES
- Q&A

INTRODUCTION

- Introduction
- Objectives
- Scope of Study

Introduction

- Accurate petrophysical evaluation of shaly sandstone reservoirs using conventional petrophysical models due to the non-linearity between log data and reservoir properties.
- Numerous empirical models for shaly sand were developed and the selection of the most suited model must be done on field-to-field basis to determine the petrophysical parameters, which in some cases, the accuracy can still be quite poor.
- Artificial neural networks utilizes the prevailing unknown non-linear relationship in data to accurately determine the certain petrophysical properties of the reservoir.
- **This study achieved a successful application of artificial neural networks to predict porosity and water saturation of a shaly sand formation.**

Objectives

- To estimate porosity and water saturation of a shaly sand formation by the conventional approach.

- To estimate porosity and water saturation of a shaly sand formation using artificial neural networks (ANN).

- To compare results of the two approaches to evaluate the feasibility of ANN application in petrophysical evaluation of shaly sand reservoirs.

Scope Of Study

Aim

- To obtain comparative results of the conventional approach and the ANN approach

Literature Review

- Review of studies about petrophysical evaluation of shaly sandstone reservoirs, neural network applications and related previous studies

Conventional

- Understanding and applying basic log interpretation and empirical relationships to estimate porosity, shale volume and water saturation.

Artificial Neural Network

- Developing ANN (Training, Validating and Testing) in MATLAB using Neural Network Fitting Tool

LITERATURE REVIEW

- Shaly Sand Evaluation
- Artificial Neural Networks (ANN)
- ANN Applications

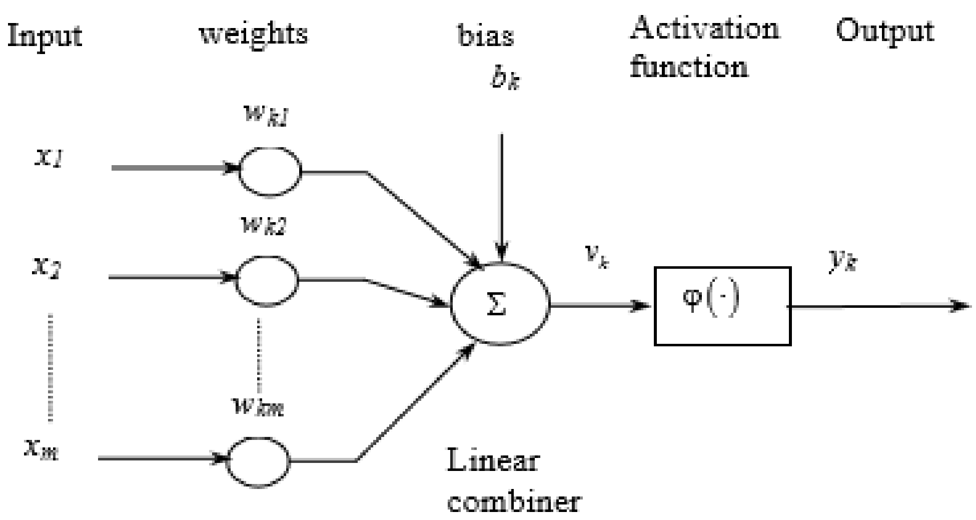
Shaly Sand Evaluation

- Log responses are affected by the presence of shale (Bassiouni, 1994).
- Shale volume or clay content has a significant impact on determination of porosity, permeability and water saturation (Bassiouni, 1994).
- Many empirical corrections have been proposed and published for estimation of petrophysical parameters in shaly sand formations (Bassiouni, 1994).
- Empirical correlations differ in terms of input variables, type of clay minerals and type shale distributions (Worthington, 1985).

Artificial Neural Networks

- McCulloch and Pitts (1943) introduced the first neural network.
- It is a machine-representative of a human brain in a way that it can attain knowledge, store knowledge and learn through a training process to solve for problems with inputs that are unseen before (Bhatt, 2002).

(Bhatt, 2002)



A Simple Neuron Model (Bhatt, 2002)

Types of Networks and Training Algorithms

- Feed-forward network

  -data travels in the forward direction only

  1. Single-layer feedforward network
  2. Multilayer feedforward network

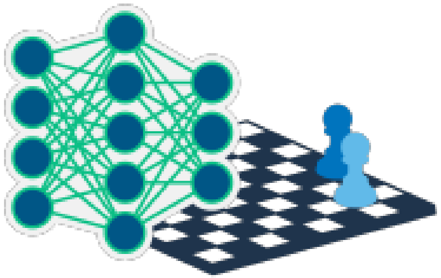
- Recurrent network

  -contains at least one feedback loop

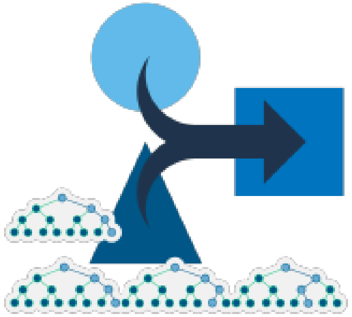
- Most commonly used Training Algorithms

  1. Levenberg Marquardt
  2. Quasi- Newton
  3. Conjugate Gradient
  4. Resilient Backpropagation

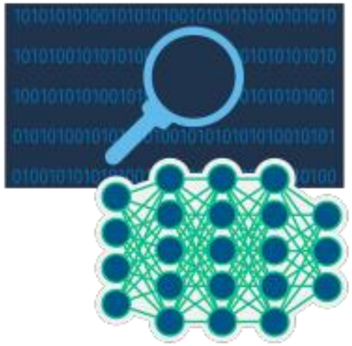
ANN Evolution



1950s–1970s
Neural Networks
Early work with neural networks stirs excitement for "thinking machines."



1980s–2010s
Machine Learning
Machine learning becomes popular.



Present Day
Deep Learning
The AI booming in many industries including Oil and Gas Exploration

Source of figures : https://www.sas.com/en_us/insights/analytics/what-is-artificial-intelligence

ANN Applications

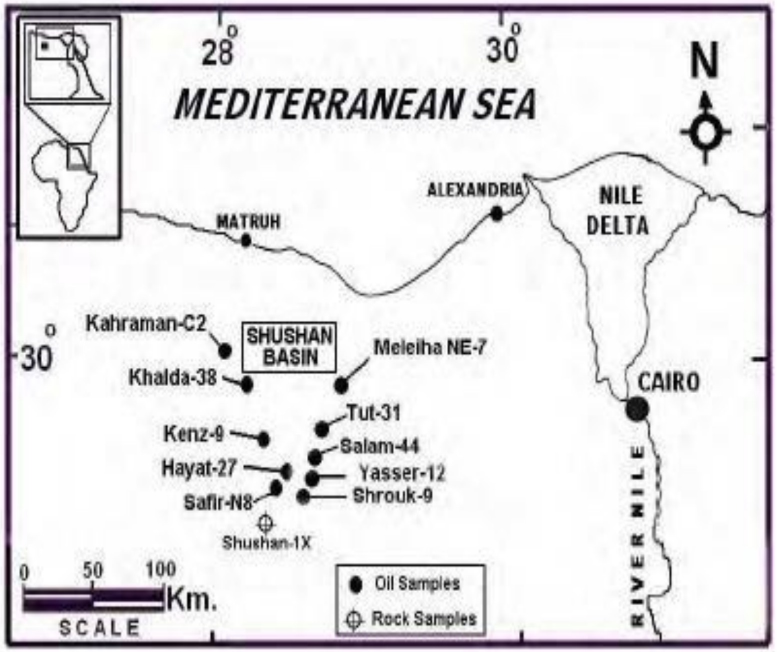
Author, Year	Field	Parameters	Used ANN type	Result
Bhatt, 2002	North Sea, Norway	Porosity, permeability and water saturation	Multilayer Networks and Committee Machines	High accuracy
Jozanikohan et al., 2015	Shurijeh gas field in Northeastern Iran	Clay content	Multilayer Networks	High accuracy
(Korjani et al., 2016	Kern River field, California	Synthetic logs	Deep Neural Networks	High accuracy

METHODOLOGY

- Available Data
- Conventional Workflow
- ANN Workflow

Available Data

- Well log data and core data from the two wells (Well A and Well B) of Upper Cretaceous shaly sand formation in Western desert, Egypt is available for the project's research purposes.
- Digitized Well Log Data of 5 logs (GR, LLD, RHOB, NPHI and PEF)
- Core data from section 8284 ft to 8373 ft.



GR-Gamma-ray , LLD-Laterolog Deep, RHOB- Density, NPHI-Neutron Density and PEF- Photoelectric Factor

Conventional Workflow

- Shale volume was calculated using GR log, and then effective porosity was calculated using shale volume calculations and other available logs.

- Water saturation was determined by the conventional approach using three different petrophysical models,

  1- Total Shale model
  2- Effective Medium model,
  3- Simandoux model

- The results of Effective Medium model was used to compare with that of ANN approach since it showed the closest to core data.

ANN Workflow

1. Data Management
   - Training data set
   - Validation data
   - Testing data set

2. Design and Training

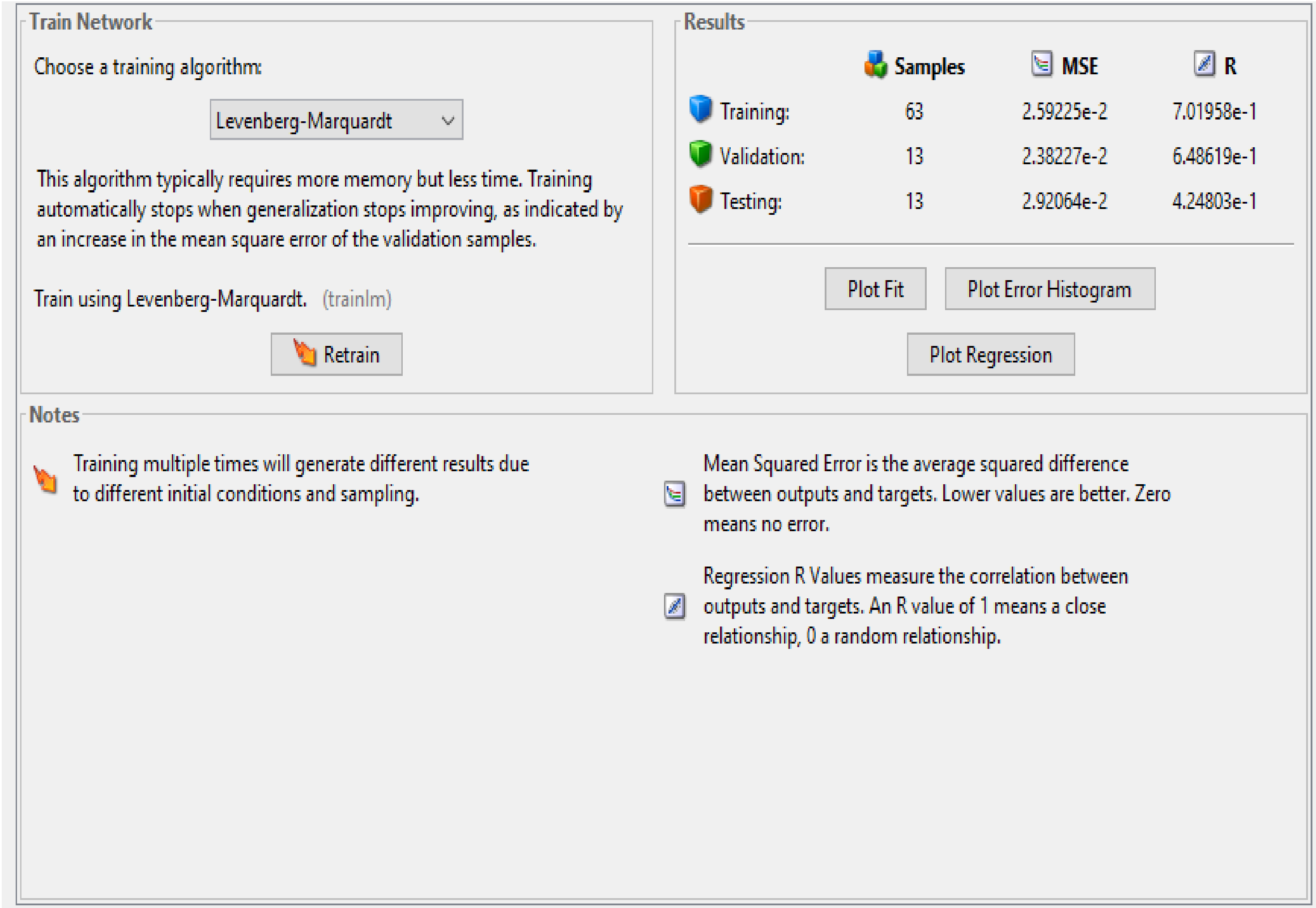
3. Validation and Testing

4. Performance Analysis

Developing the ANN

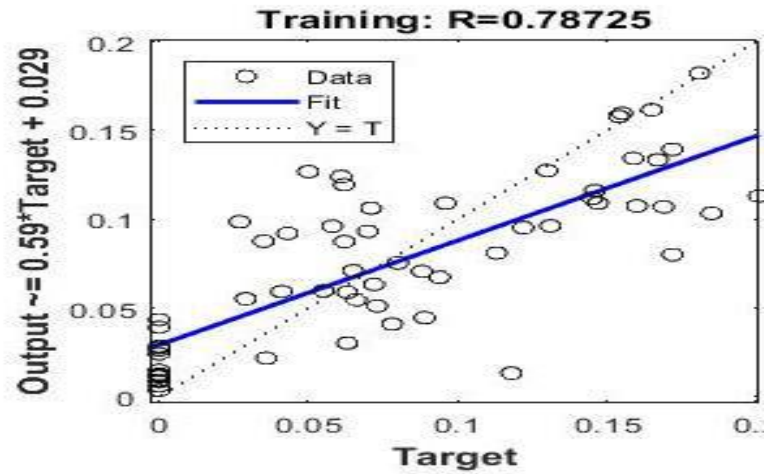
- A two-layered feedforward network was developed to be trained with the available data.
- A variety of network designs were tested by trial and error to select the ones with best accuracy in terms of performance and regression.
- The accuracy or the performance of the network is measured by Mean Squared Error (MSE), the closer the MSE is to zero, the better the performance of the network.
- The training algorithm used in this project was Levenberg-Marquardt as previous studies of ANN applications in petrophysical prediction have shown to have successful results using this algorithm.

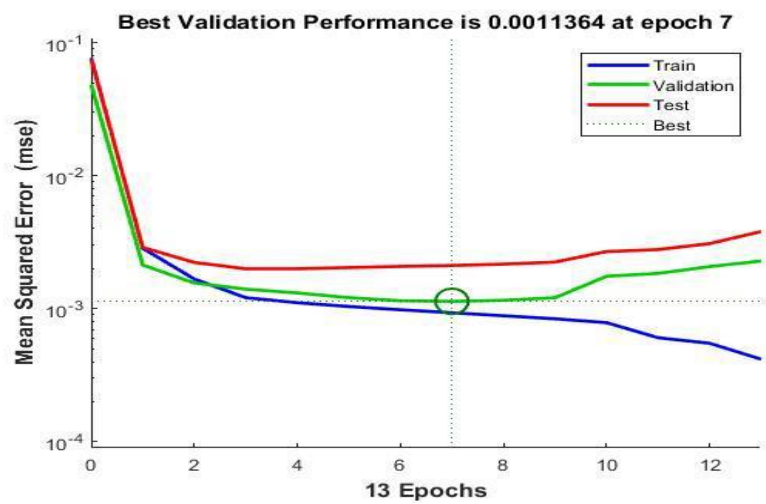
Training and Testing the ANN



The Training Interface of MATLAB Neural Network Fitting Tool

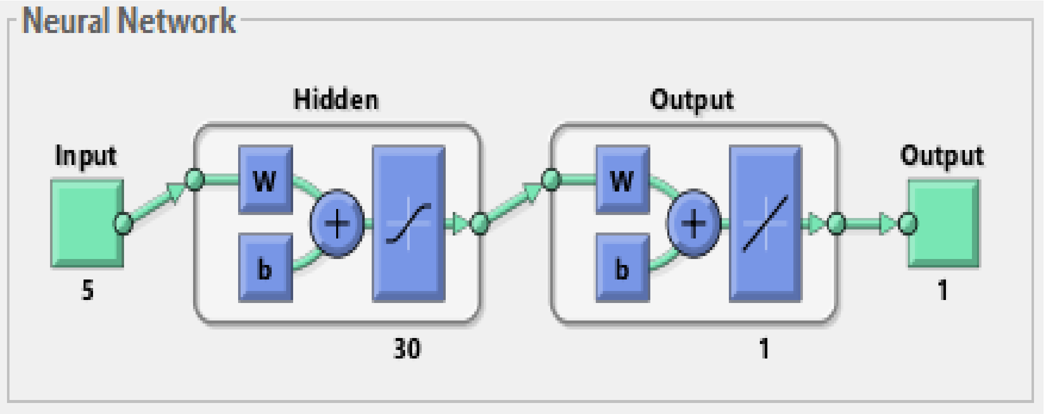
Testing and Testing the ANN



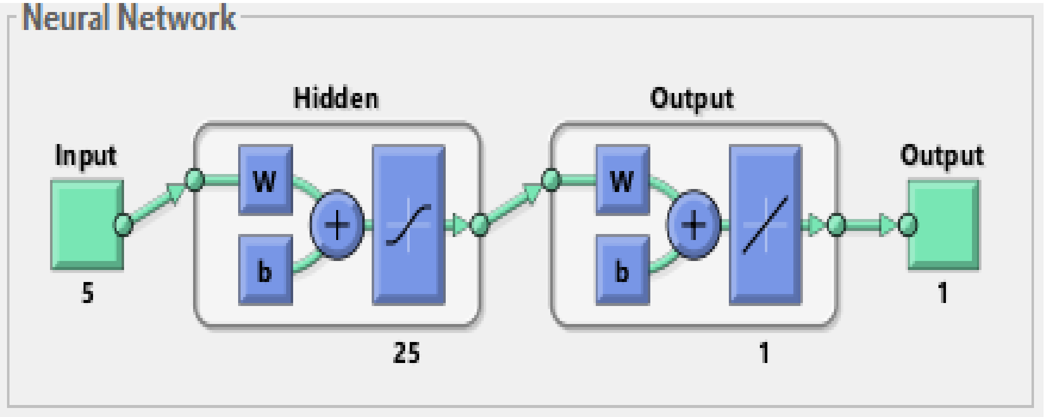


Plots of the Training Interface of MATLAB Neural Network Fitting Tool

ANN Design



Network Structure Designed for Porosity Estimation



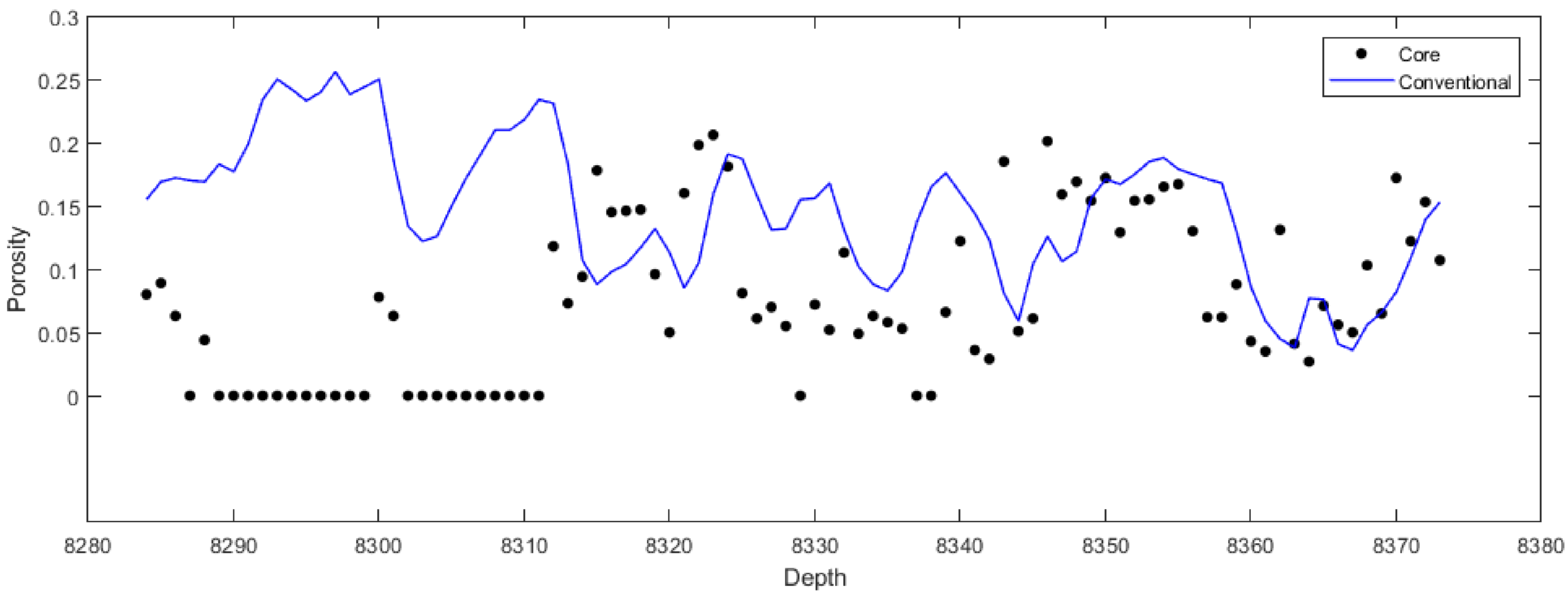
Network Structure Designed for Water Saturation Estimation

RESULTS AND DISCUSSION

- Conventional Approach
- Neural Network Approach
- Comparison Between Two Approaches

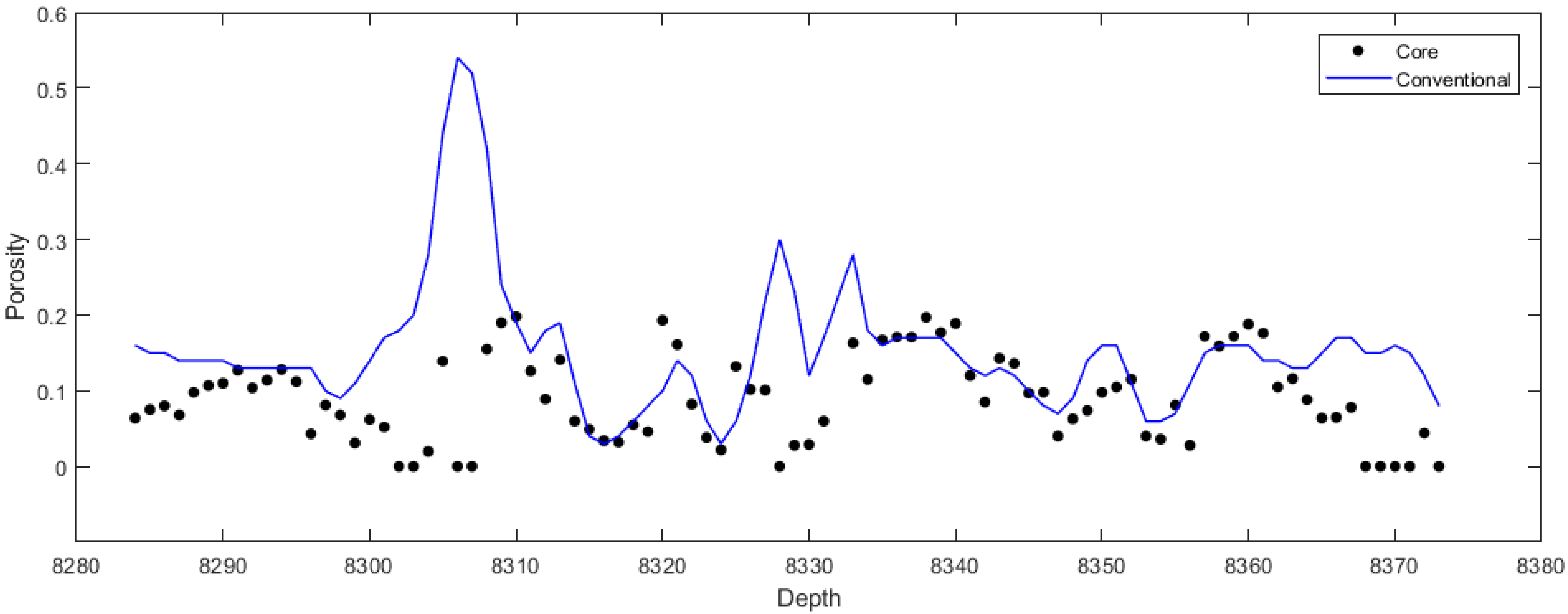
Conventional Approach
Porosity-Well A

Porosity was determined by the conventional approach and compared with the core data.



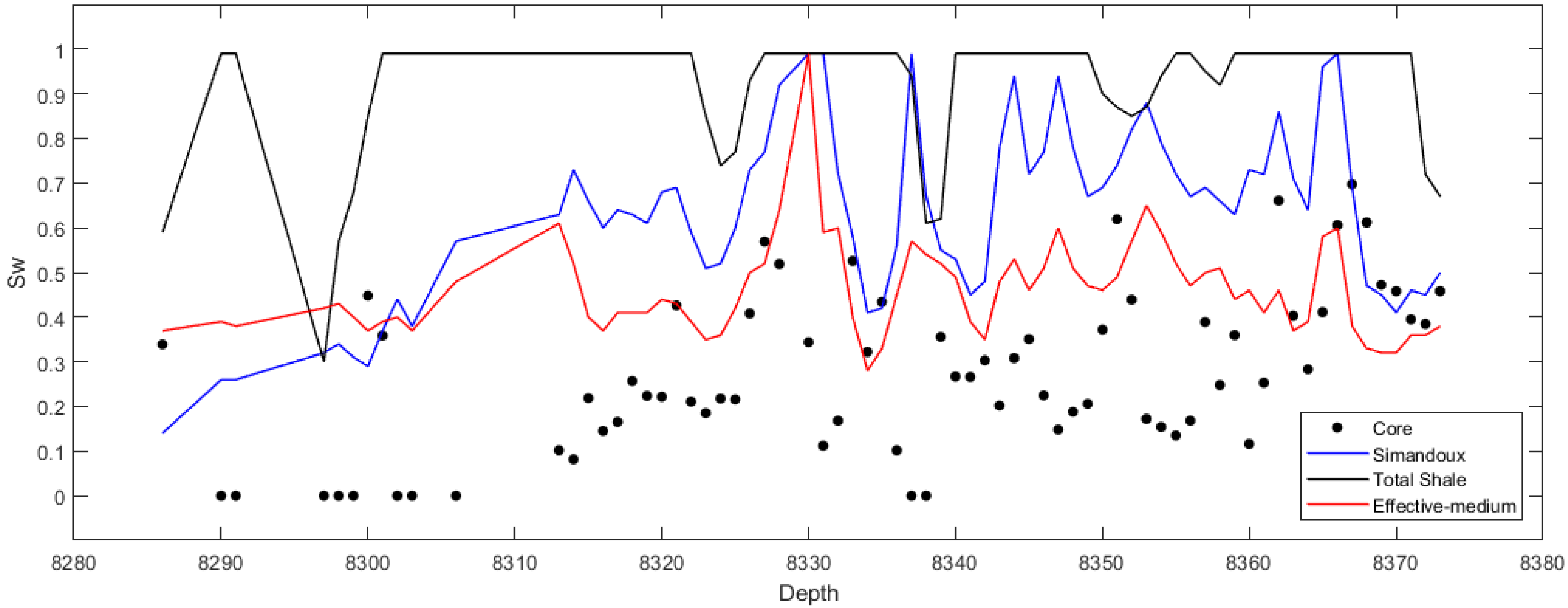
Log-derived Porosity versus Core Porosity, Well A

Conventional Approach
Porosity-Well B



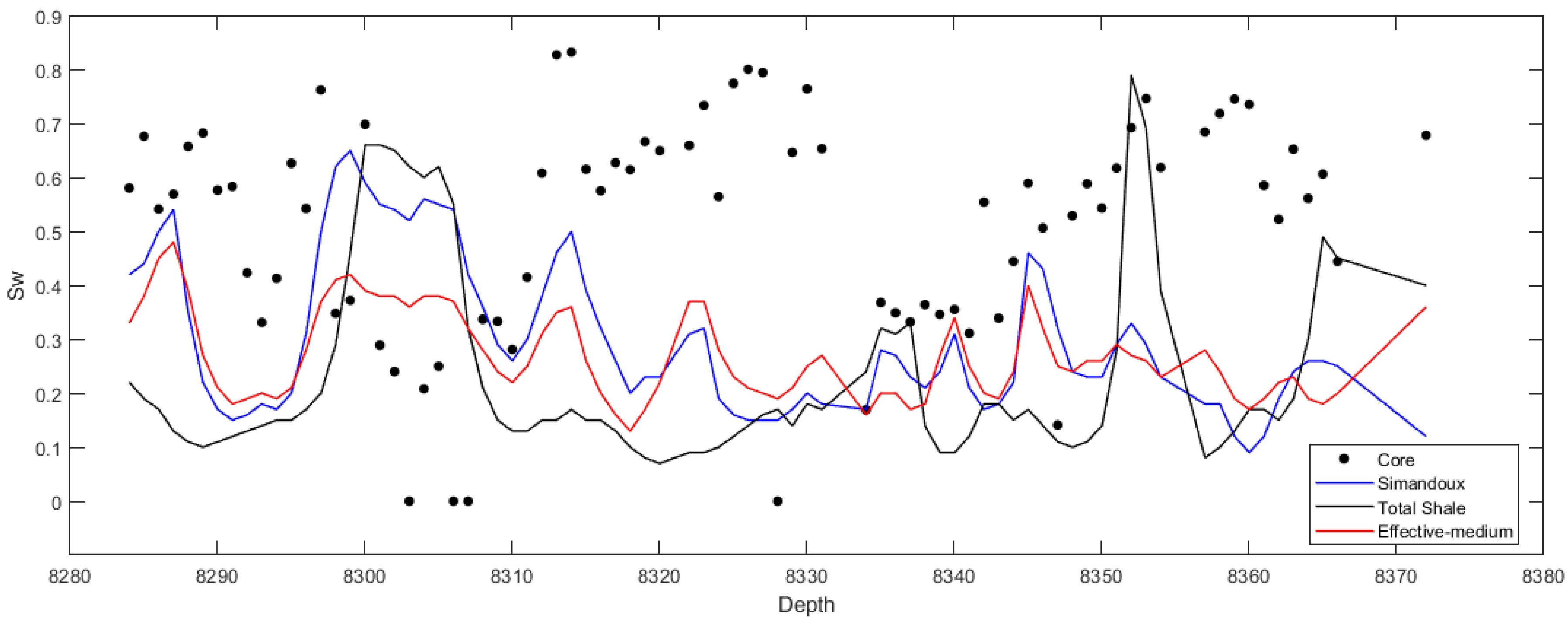
Log-derived Porosity versus Core Porosity, Well B

Conventional Approach
Water Saturation-Well A



Water Saturation calculated by Different Models, Well A

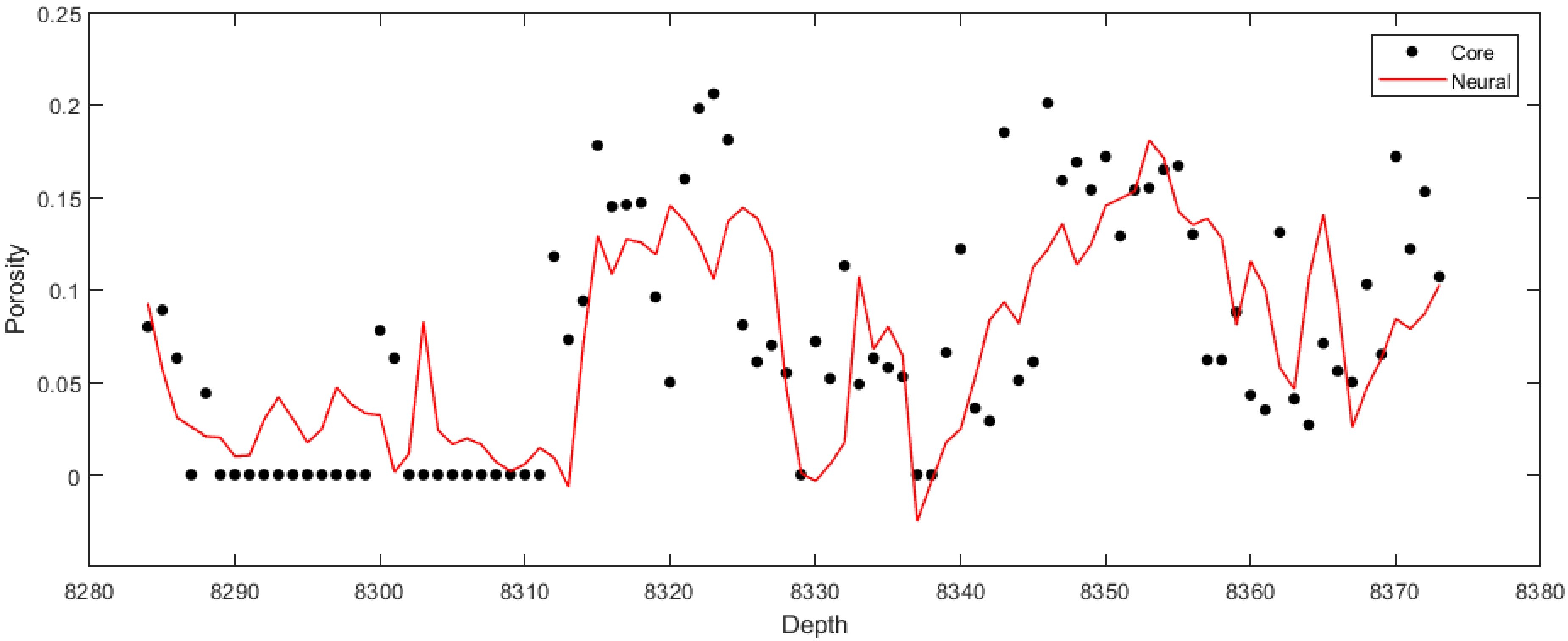
Conventional Approach
Water Saturation-Well B



Water Saturation calculated by Different Models, Well B

Artificial Neural Network Approach
Porosity-Well A

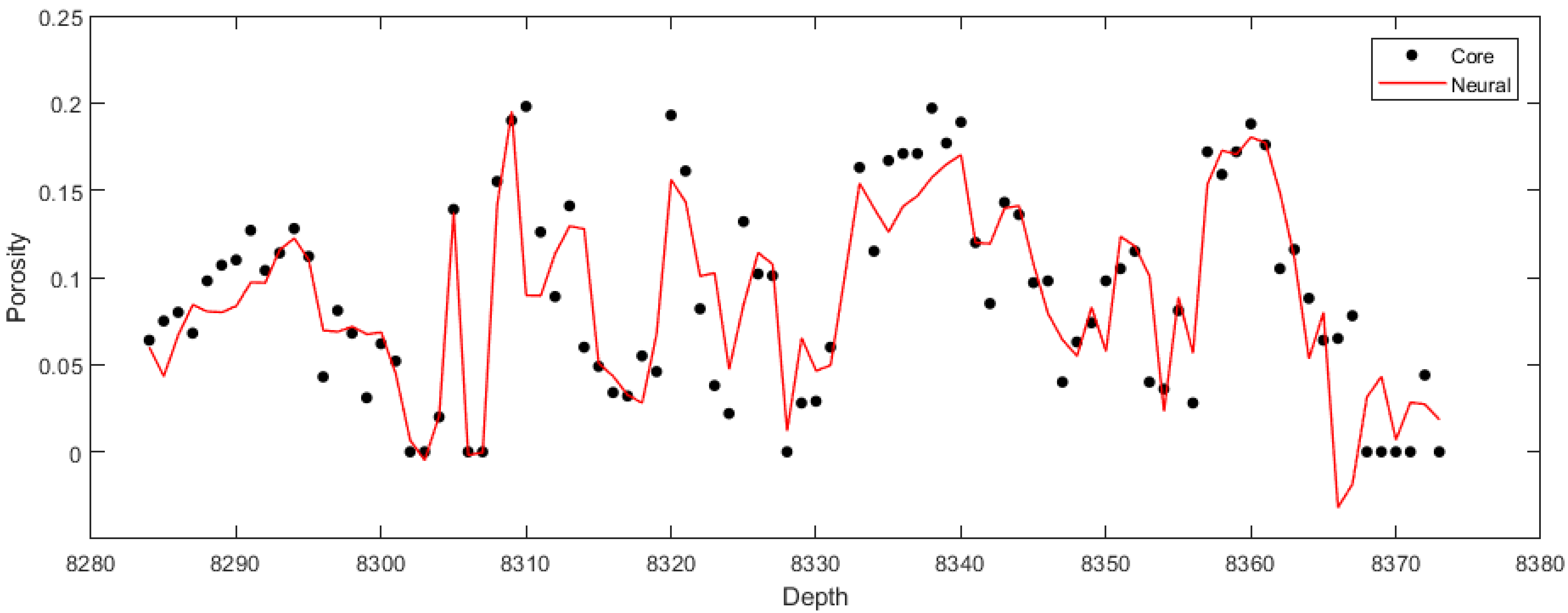
Two neural networks were successfully developed, trained, validated and tested. The first network predicted porosity for Well A with a mean squared error of 0.002209.



Neural Network-predicted Porosity versus Core Porosity, Well A

Neural Network Approach
Porosity-Well B

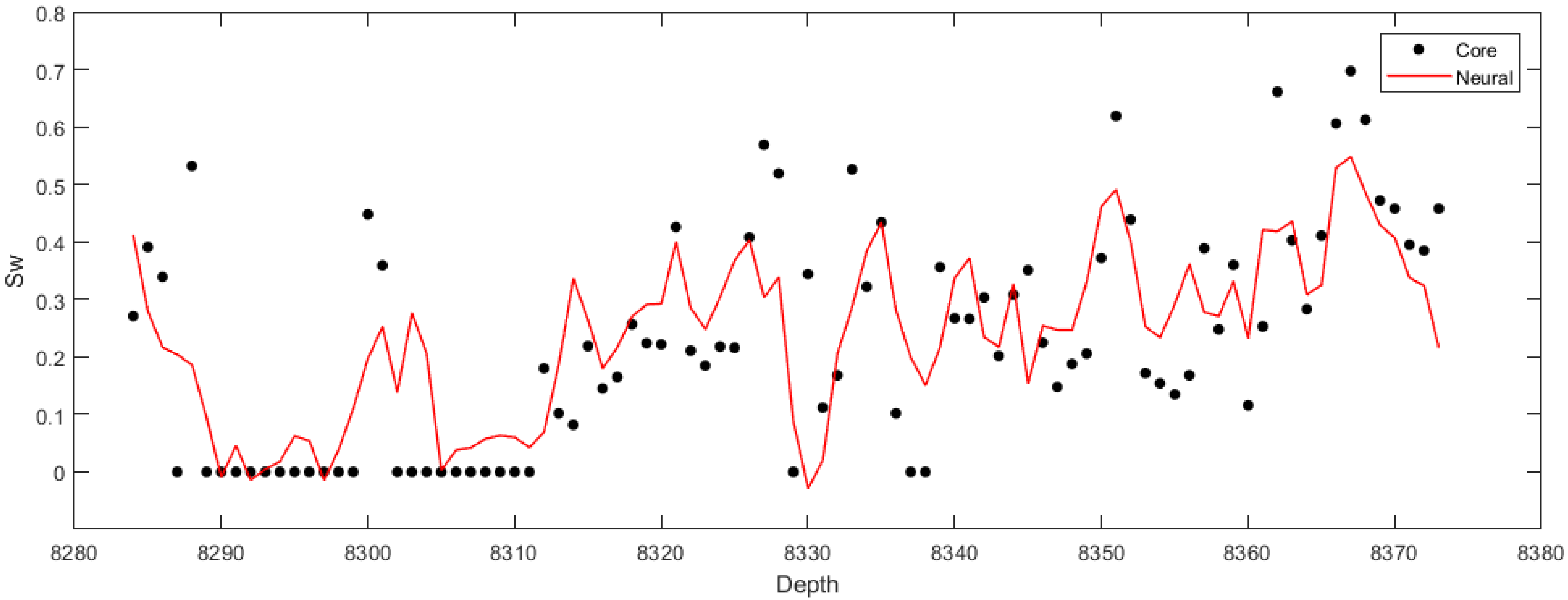
The first network predicted porosity for Well B with a mean squared error of 0.002771.



Neural Network-predicted Porosity versus Core Porosity, Well B

Neural Network Approach Water Saturation-Well A

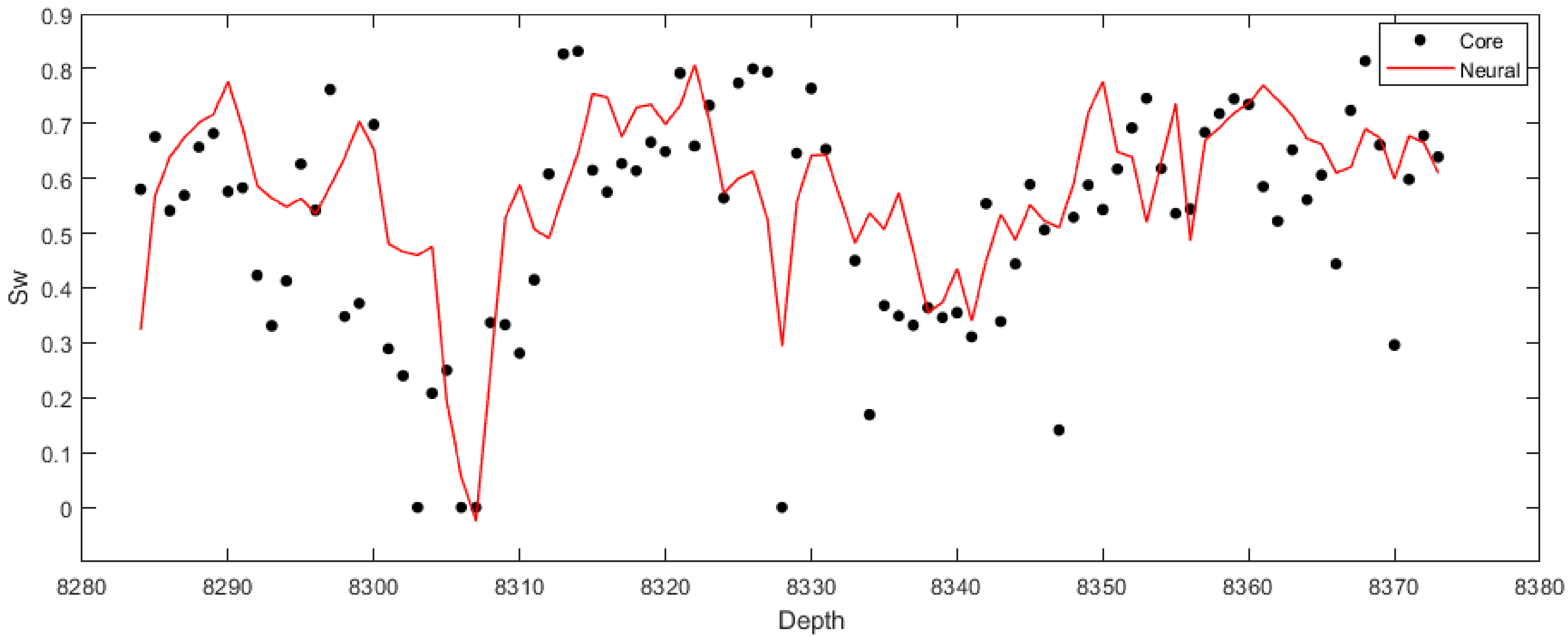
The second network predicted water saturation for Well A with a mean squared error of 0.02141.



Neural Network-predicted Water Saturation versus Core Water Saturation, Well A

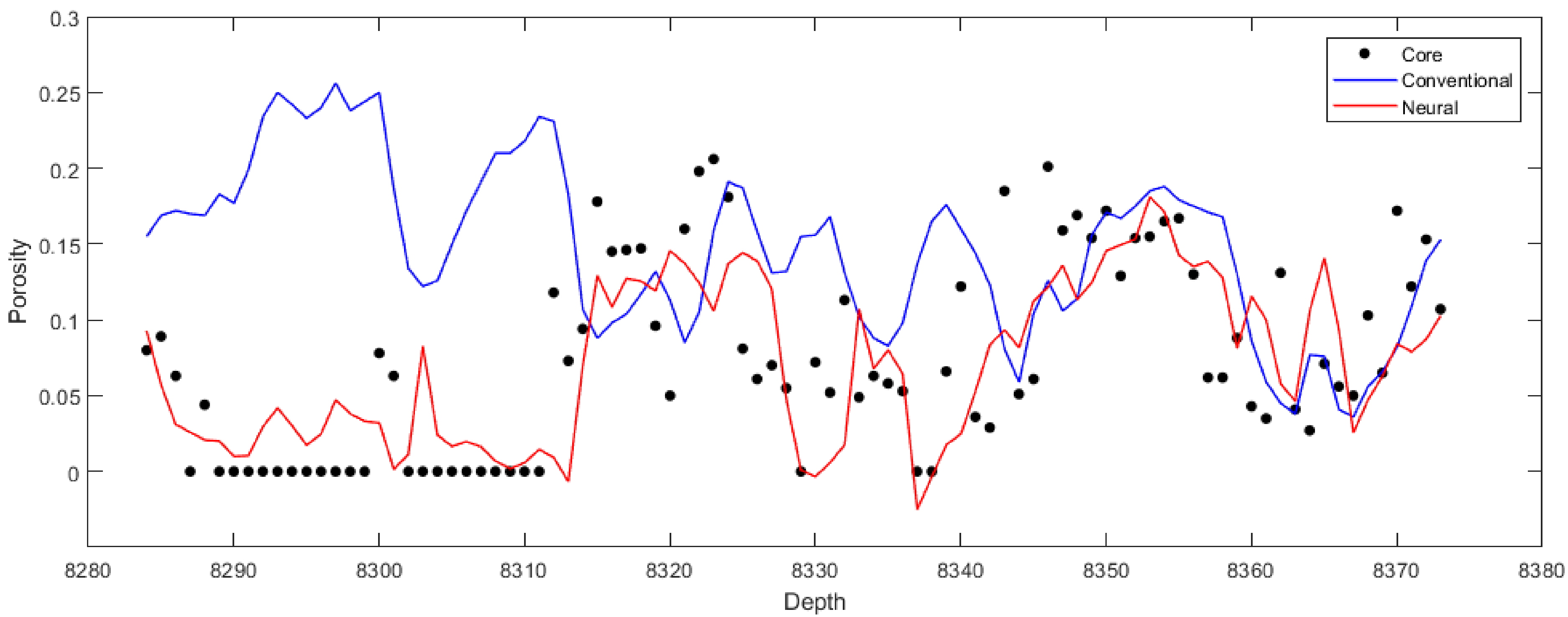
Artificial Neural Network Approach
Water Saturation-Well B

The second network predicted water saturation for Well B with a mean squared error of 0.02921.



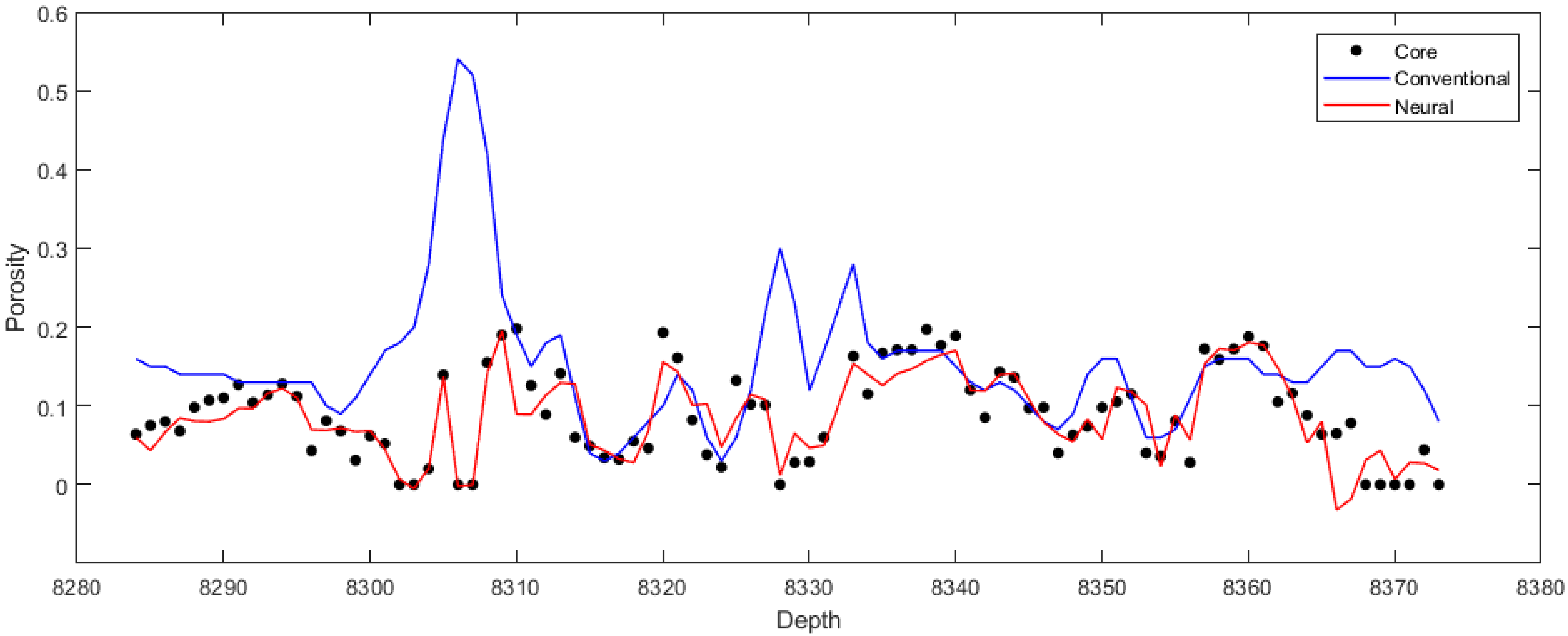
Neural Network-predicted Water Saturation versus Core Water Saturation, Well B

Comparison Between Two Approaches Porosity-Well A



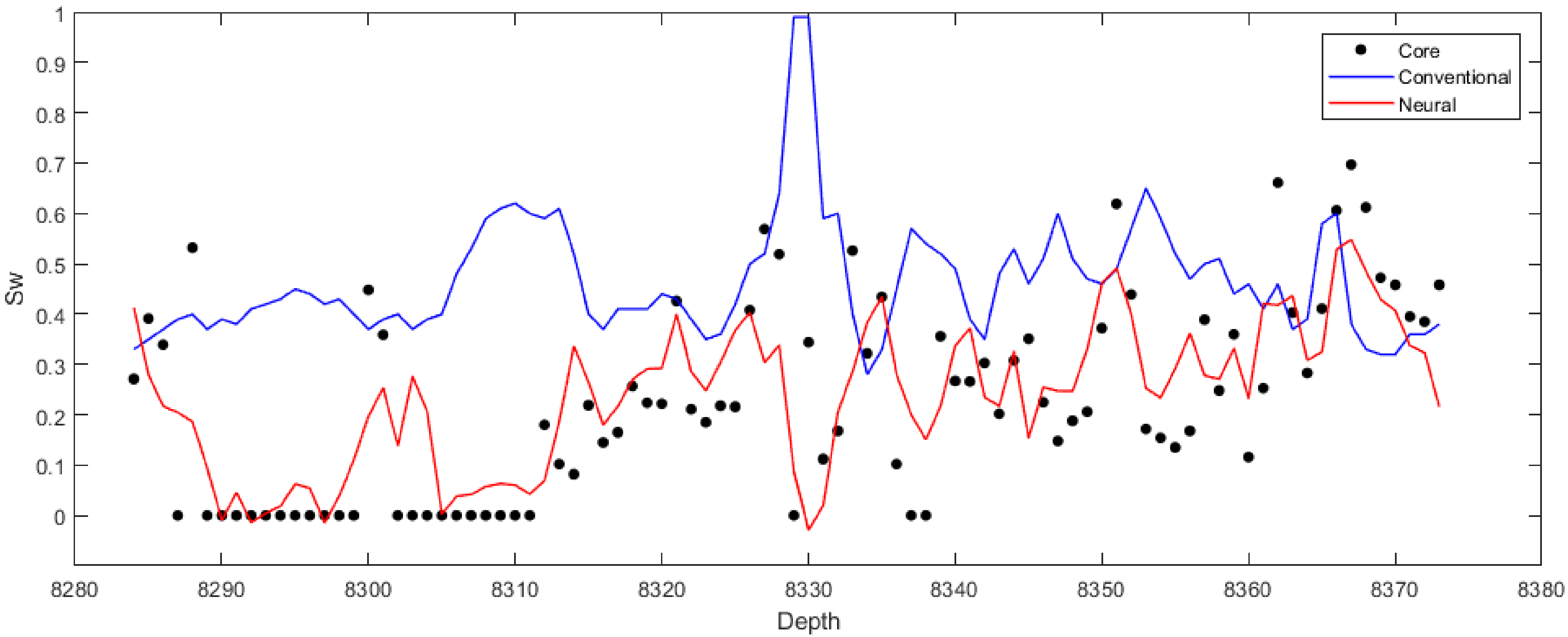
Porosity Comparison between Neural Network and Conventional Approaches, Well A

Comparison Between Two Approaches Porosity-Well B



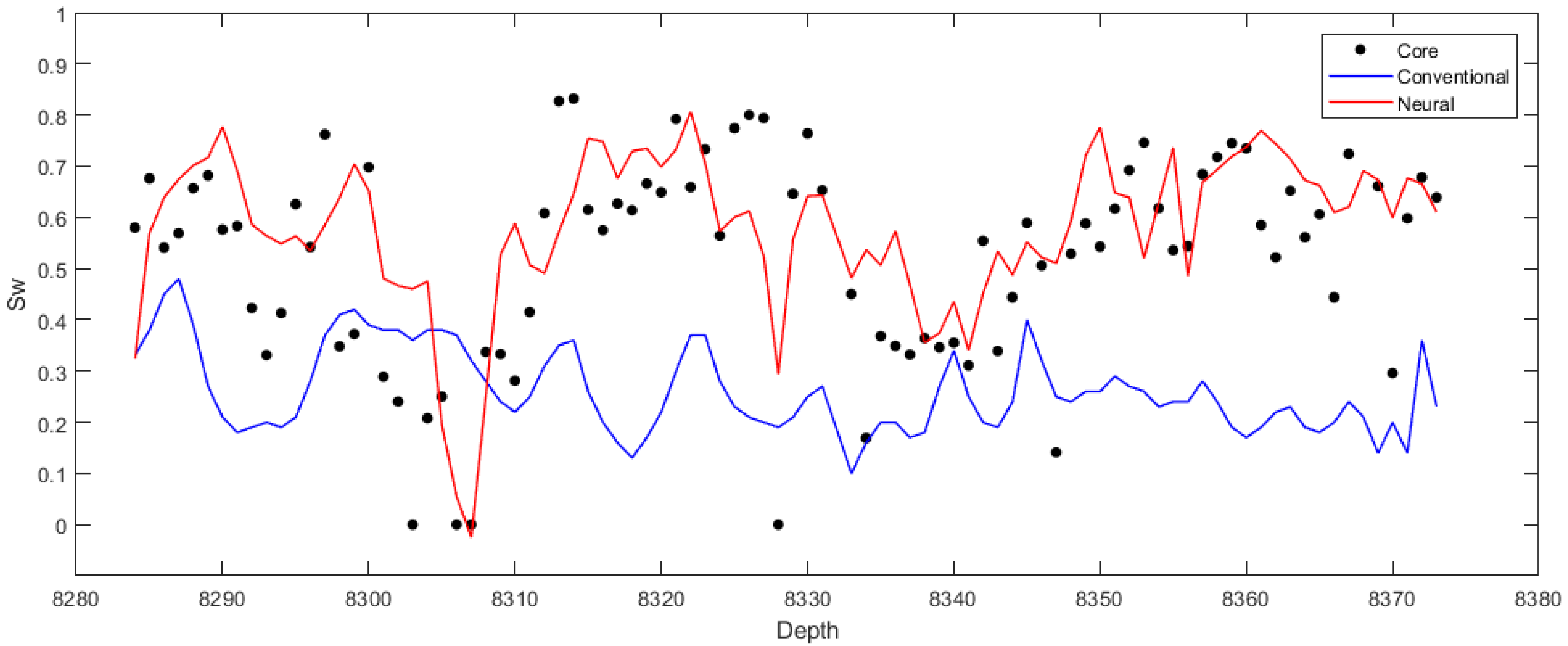
Porosity Comparison between Neural Network and Conventional Approaches, Well B

Comparison Between Two Approaches Water Saturation-Well A



Water Saturation Comparison between Neural Network and Conventional Approaches, Well A

Comparison Between Two Approaches Water Saturation-Well B



Water Saturation Comparison between Neural Network and Conventional Approaches, Well B

Comparison of Average Values

	Avg Porosity		
	Core	ANN prediction	Calculated
Well A	0.133	0.125	0.155
Well B	0.12	0.10	0.16

	Avg Water Saturation					
	Core	ANN prediction	Effective medium	Total shale	Simandoux	Archie
Well A	0.33	0.31	0.39	-	0.58	0.54
Well B	0.52	0.47	0.55	0.59	0.57	0.62

Conclusion

- Project's objectives were successfully achieved.

- For both porosity and water saturation, it was observed that the ANN approach obtained significantly better accuracy than conventional approach in both wells.

- In conclusion, the application of ANN in the petrophysical evaluation of shaly sand formation was proven to be a feasible option as supported by the project's results.

Recommendation

Limitations

- Limited knowledge on advanced mathematics for a wide range of neural network algorithms to be explored while designing the neural networks, which may give equal or better performance
- Uncertainties in the available data such as the background of the core data and other reports

Recommendations

- A deeper understanding of neural network algorithms should be incorporated.
- Larger volume of field data with a full set of supporting background documents of the field should be in place to enhance the training and validation processes in developing neural networks.

THANK YOU

Q & A

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