Geomechanical Modelling Using Artificial Neural Networks Combined With Geostatistics

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ABSTRACT

The principal minimum horizontal stress plays an important role in the study of reservoir characteristics, modeling of oil and gas reservoir, drilling, production and stimulating wells. However, it is currently not possible to measure the minimum horizontal stress along the wellbore as a geophysical parameter logging. Minimum horizontal stress is measured by leak-off test (LOT) at only several points in a well. In order to have the values all along the wellbore, experimental formulas were established to determine the minimum horizontal stresses for different fields. Then these formulas must be calibrated with LOT data whose number is usually limited, even sometimes unavailable. On the other hand, the empirical formulas of one field might not be accurate for another.

This study presents a new approach to solve the problem of minimum horizontal stress estimation by a combination of artificial intelligence and geostatistics. The method consists of using artificial neural network (ANN) to build a model of minimum horizontal stress estimation from relevant parameters such as true vertical depth, pore pressure and vertical stress, then combined with Kriging interpolation to obtain the distribution in space of the minimum horizontal stress. Hence, this method can estimate the minimum horizontal stress with a limited amount of available data and therefore we do not need to drill new wells or to find empirical formulas for each survey area. The method was then applied in a case study involved real geomechanical dataset of Hai Thach - Moc Tinh field in Nam Con Son basin, Vietnam.

1.   Introduction

Geomechanics and geophysics are essential tools for reservoir simulation, for assessing hydrocarbon reserves, as well as for drilling and production. In a geomechanical model, stress information is particularly important, especially the

minimum horizontal stress (S_{hmin}) which is obviously a significant parameter used for many kinds of work in petroleum engineering.

Theoretically, S_{hmin} can be determined by equation relating to other geomechanical parameters such as pore pressure and vertical stress [1]. On the other hand, empirical formulas were also established to determine minimum horizontal stress indirectly through sonic wave velocity measured from logging [2]. In reality, S_{hmin} values determined from these empirical formulas still need to be calibrated with values obtained from the leak-off test (LOT). However, the main inconvenient of LOT is the limitation of data because LOT is normally conducted at some discrete points along the wellbore, and the number of wells taking LOT data is often limited. Consequently, the small amount of LOT data may reduce the accuracy of the calibration. Moreover, as each field has its own geological characteristics, the application of the same formulas from one field to another will lead certainly to errors.

With the development of Artificial Intelligence, new methods based on artificial intelligence tools applied to technical fileds are increasingly popular. As one of artificial intelligence tools, artificial neural network (ANN) helps computers perform tasks for human with self-learning thinking.

Dowd and Saraç (1994) presented a brief description of ANN and explained the basics of the feedforward back-propagation network and the use of ANN in geostatistics. The multilayered feedforward back-propagation algorithm was used to predict the desired variogram values. This purely mathematical research concluded that geostatistical simulation via neural network is a possibility [3].

M. Kanevsky et al. (1996) used ANN and geostatistics methods for environmental mapping. The authors drew a map of the nuclear radiation distribution around a reactor where a nuclear accident happened in 1986. From the radioactive data measured at various points, the geostatistical interpolation method was used to draw a map of the distribution of nuclear radiation of the whole region. Besides, another map was made using artificial intelligence. The authors compared geostatistical and ANN models by using cross-validation technique as well as validation data sets. The result showed that the method of using ANN was very promising in environmental and Earth sciences [4].

Sadun Arzuman (2009) approached the method of finding missing logs with the classical calculation method, ANN method and geostatistics method. The author used the Neutron Porosity log and Density log to estimate Sonic log and used seismic data to predict other parameters of the reservoir by ANN [5]. However, both Kanevsky's [4] research and Arzuman's [5] research used independently ANN and geostatistics. They did not develop models combining ANN and geostatistics.

S. Ali Moasheri et al. (2013) presented a study using simultaneous geostatistics and ANN to forecast the "SAR" (Sodium adsorption ratio) to assess the groundwater pollution. The authors used EC (Electrical Conductivity), PH (Potential Hydrogen), TDS (Total Dissolved Solid), TH (Total hardness) parameters as input parameters to train neural network, the target data of the model was SAR. These parameters were also analyzed by geostatistics to show their distribution as well as their variogram calculations. The interpolation graphs of these indices were plotted by Kriging method. The results indicated that ANN-Kriging combination method could predict SAR from data that were easily accessible with low cost and time such as PH, TH, TDS, EC [6].

Hashemi et al. (2014) used the Multiple-point statistics to model the complex geological structure. Based on the survey boreholes, the data was used to construct images of the area's facies, then the images were studied and analyzed using neural network [7].

Soares et al. (2016) presented a method called Incremental Gaussian Mixture Network in reservoir simulation [8]. The main point of this method is to change the structure of the neural network by adding Gaussian algorithm into hidden layers for training instead of using the usual training functions.

Ricardo Ríos et al. (2016) presented a study assessing the landslide hazard in the state of San Salvador, El Salvador by combining ANNs and geostatistics techniques. In order to predict landslide risk, the authors used input parameters such as Geomorphology, Slope gradient, Rainfall intensity, Peak ground acceleration, Fault distance... to build ANN model, the output was the probability of landslide. The data sets are divided into Train set, Test set and Validation set. The Train set was randomly selected to train the ANN model, then the Validation set was used for the Kriging model of geostatistics. By cross-validation technique, the best regression model is

used to build landslide hazard map. Though the problem of modeling landslide prediction was inherently complicated, the model combining ANNs and geostatistics achieved up to 80% accuracy [9].

Thereby, combining ANN with geostatistics has been approached in various studies in literature. However these studies were mainly purely mathematical demonstration of the possibility of this combination and were applied principally in geotechnical or environamental domains. The contribution of this paper is to present a new modeling workflow which consists of combining ANN with Kriging interpolation to solve the above mentioned problem regarding the minimum horizontal stress. The prediction parameter is the minimum horizontal stress and the training parameters are depth, pore pressure and vertical stress. The influence factors such as strata, depth and number of wells were also evaluated. This method of combining ANN and geostatistics allows petroleum engineers to build accurate geomechanical model while having just a few data wells. Obviously, building a normal Kriging interpolation model requires data from at least three wells but with the new approach, this study did successfully use only data from one well to build a interpolation model similar to the one obtained using Kriging method alone.

2. Methodology

2.1. Workflow

Due to the complexity of this study, a schematic diagram step by step of this research is presented in **Fig. 1**. The models using ANN were generally built with the same steps, but the data was different for each case. Firstly, the influence of parameters such as depth, number of wells and number of stratifigraphies on the ANN models were studied. Secondly, these results will help to develop a model using combination of ANN and geostatistical method which in this study is the Kriging interpolation. A comparison between the results of this model with the results given by only geostatistical method was also effectuated so that the advantages of this new workflow can be drawn.
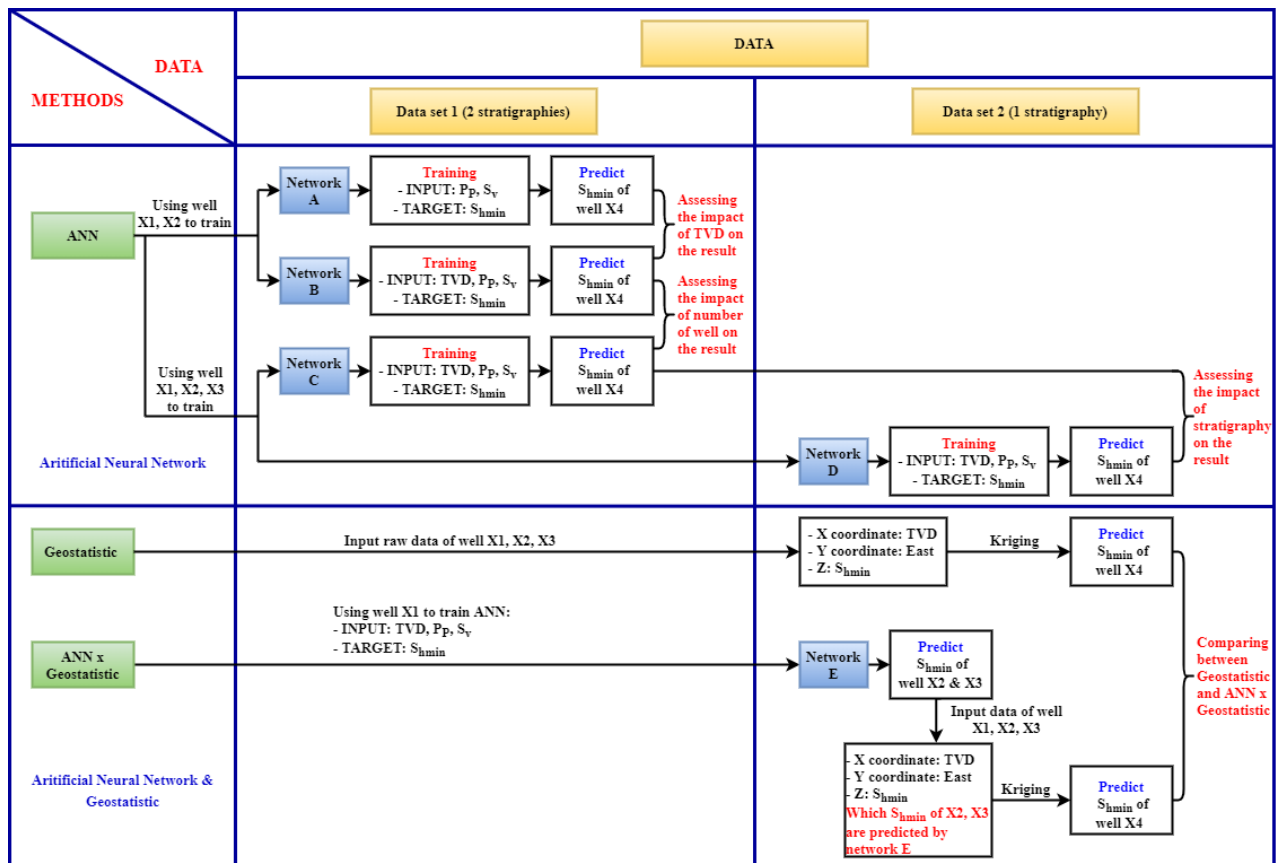
Figure 1 – The general workflow proposed in this research.

2.2. Data set

This study collected logging data from 4 wells, which were denoted as X1, X2, X3 and X4. These wells belong to Hai Thach - Moc Tinh Field in the continental shelf of Southeast Vietnam. **Fig. 2** shows a view of these 4 wells in a two-dimensional space.

The data set included the geomechanical parameters of the wells, however, in this study's scope, only 4 geomechanical parameters were used as follows:

- TVD – True Vertical Depth – m
- P_P – Pore Pressure – ppg
- S_v – Vertical Stress – ppg
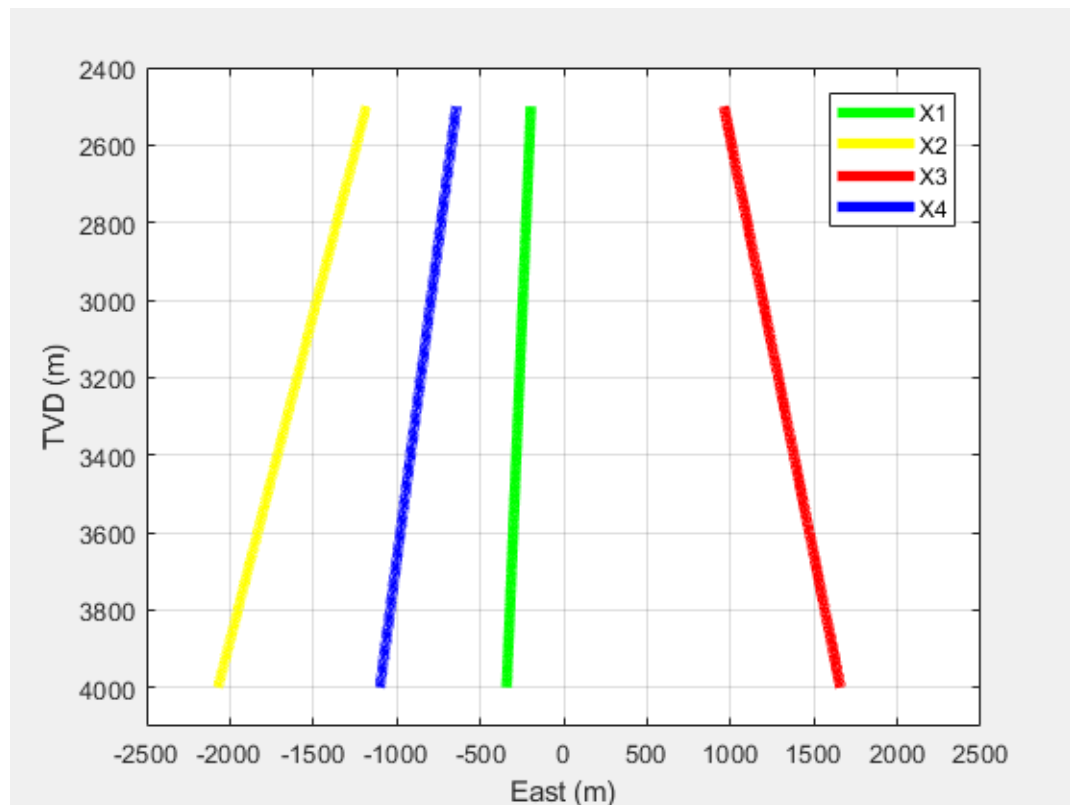- S_{hmin} – Minimum Horizontal Stress – ppg

Figure 2 – A view of the wells X1, X2, X3, X4 from the south on the TVD projected on a vertical West-East plane.

These parameters were chosed because underground formations are subject to a vertical compressive stress caused by the weight of the overlying strata, and also horizontal stresses due to the confining lateral restraints. In addition, the in-situ principal stresses are usually anisotropic and assumed to be aligned vertically and horizontally **(Rasouli et al., 2011)** [10]. The profiles of P_P, S_V and S_{hmin} for four wells are presented in **Fig. 3.**
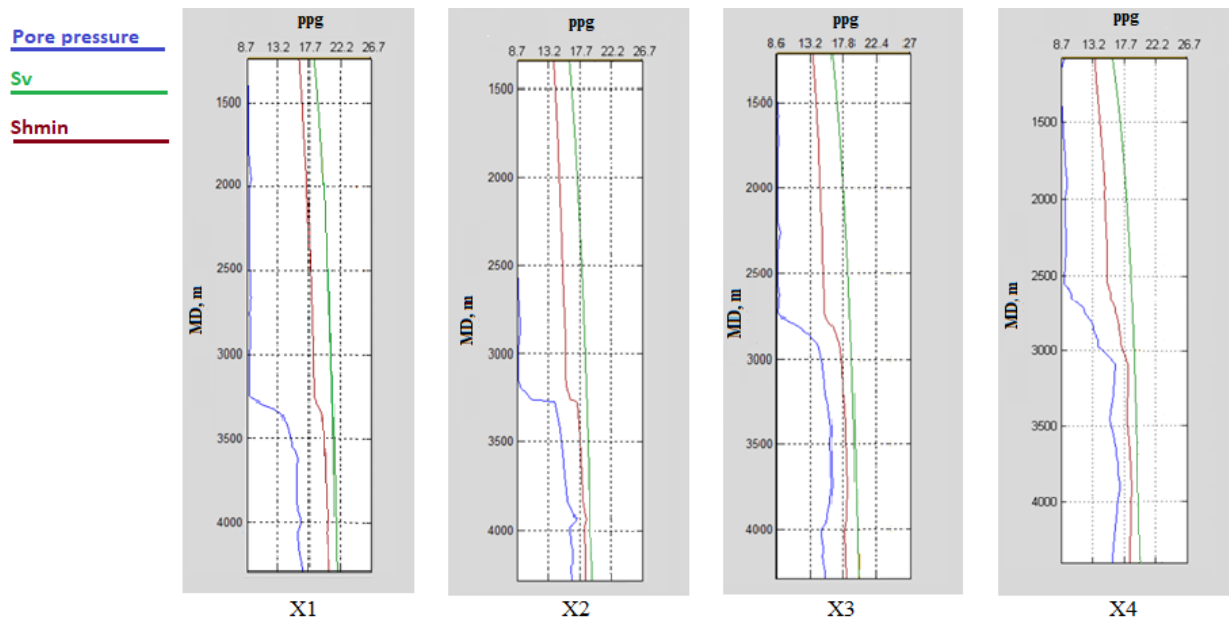
Figure 3 – Profiles of P_P, S_V and S_{hmin} for four wells X1, X2, X3 and X4.

As the depth interval of sequential stratigraphy might not be the same for each well, mud windows were established in **Fig. 4** in order to determine the range of data that should be taken so that the influence of stratigraphy could be studied. Three fundamental parameters govern the value of the density while drilling: the maximum pore pressure of the considered phase, the minimum fracturing pressure of the considered phase and the critical stability density of each formation. The Mud Window is the density range between pore and fracturing pressures **(Chalez, 1999)** [11]. However, a safe and intact Mud Window is the density range between the collapse pressure (or breakout pressure), at which the wellbore collapses due to the pressure difference between the formation and the well, and fracturing pressure. Two distinctive stratigraphies were observed from the mud windows in Fig. 4.
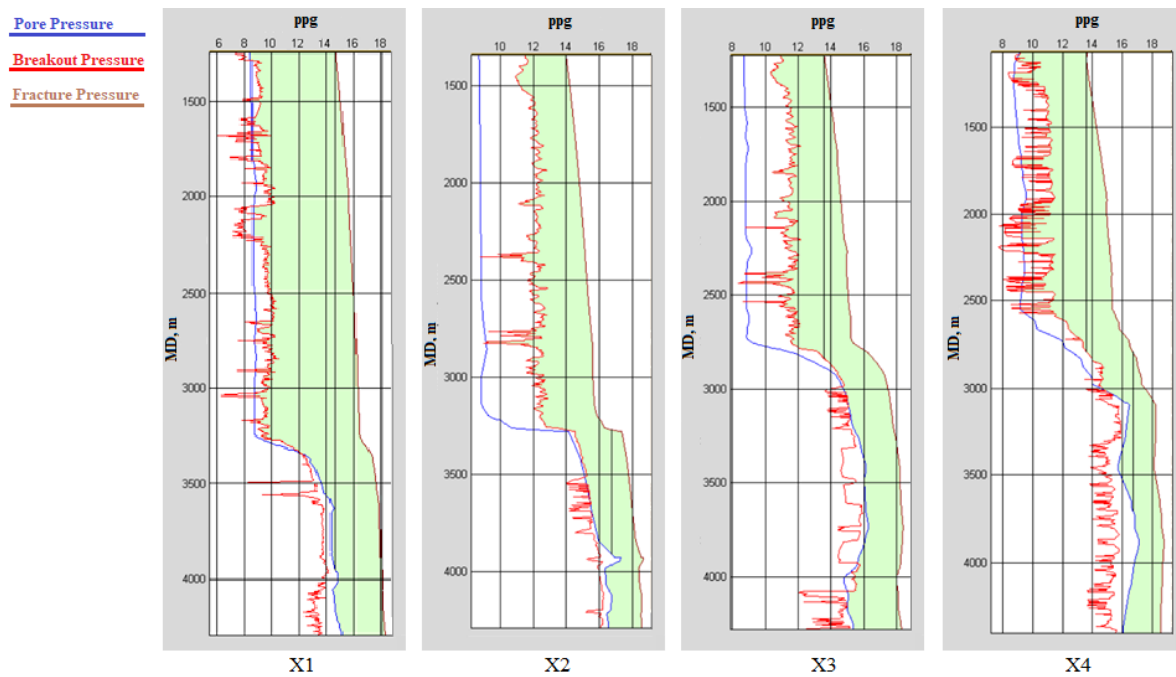
Figure 4 – Mud windows of four wells X1, X2, X3 and X4.

Hence the data were divided into two groups in order to study the influence of stratigraphic uniformity on the results:

- Data set 1: which included logging data of the wells from 2500 m to 3500 m. Data in this depth range belongs to the transition between the 2 stratigraphies. Data set 1 has 2000 data points and the data was taken every 0.5 m.
- Data set 2: which included logging data of the wells from 3300 m to 4000 m. Data in this depth range belongs to the second stratigraphy from the top down. Data set 2 has 1400 data points and the data was also taken every 0.5 m.

The number of data points of two data sets is eligible to build models and train artificial networks.

2.3.   Estimation workflow of minimum horizontal stress using artificial neural networks

ANN is an artificial information processing system inspired by how neural networks work in the human brain. ANN is one of the techniques of artificial intelligence applied to solve specific problems of classification, pattern recognition and data

prediction. ANN converted input data into output data by calculations performed in neurons. However, in order for the output value to be accurate and reliable, the network needs to be built and trained to describe accurately the nature of the relationship between the output data and the input data.

A typical artificial neural network has three main parts: Input layer; Hidden layers and Output layer (**Fig. 5**).

- Input layer: The input data is entered as vectors, and the number of vectors corresponding to the number of neurons of this input layer.
- Hidden layers: Hidden layers connect the input value to the output value. The neurons in hidden layers are mainly responsible for interpreting the input layer's neurons and then sending the information to the output layer's neurons.
- Output layer: The output data is organized as vectors, and the number of vectors corresponding to the number of neurons of this output layer.

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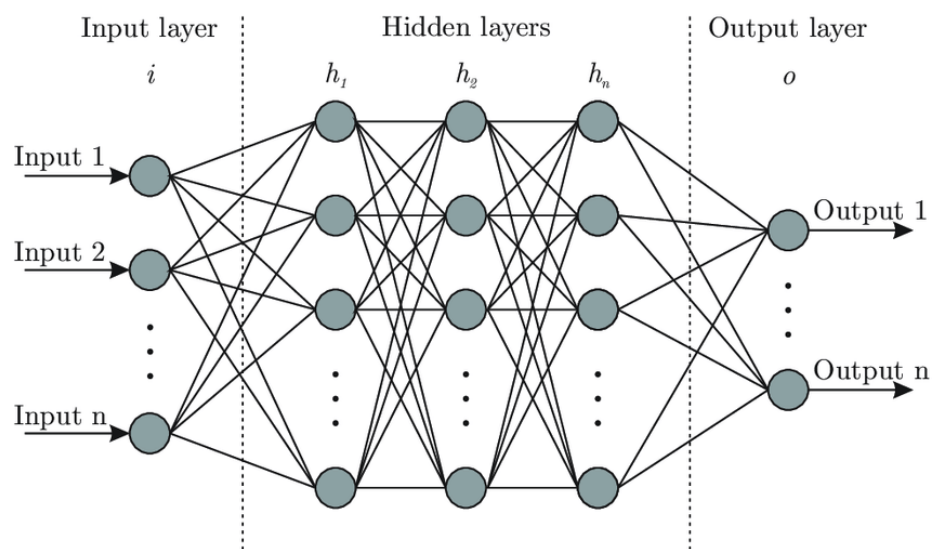
- **Figure 5** – A multilayered neural network [13].

The network is built through network training process which essentially adjusts weights through epochs so that the output values are reliable and have small error compared to the actual values. At the end of the training, the weight value will be saved and used to forecast output data when other input data is available.

Gradient descent algorithm is the most widely used algorithm for optimizing artificial neural networks by updating weights and bias. The Gradient descent formula is given as follows:

$$x_{t+1} = x_t - \gamma f'(x_t) \tag{1}$$

Where: x_{t+1}: The next value of the point to find;

x_t: Current point value;

γ: Learning rate;

f'(x_t): Value of the derivative function at the point in question.

In this paper, multilayered feedforward neural networks were used mainly for estimating minimum horizontal stress. A multilayered feedforward neural network is useful while analysing non-stationary data which a complex trend. Levenberg-Marquardt training function was used for training the networks because of the fact that the error of Levenberg-Marquardt algorithm reduces more rapidly than other existing algorithms.

Based on the basic theory of ANN, the following workflow was proposed to develop ANN models in this study:

Step 1: Data collected and analyzed

Data of the three wells X1, X2 and X3 were used to build artificial neural networks. Parameters including TVD, P_P and S_v are selected as input and the minimum horizontal stress is taken as the output of the networks. However, depending on the purpose of the network, there will be different data sets for each model, and this will be presented more in detail in step 2. Once the ANN models are built, the data of the remaining well, X4, will be used to estimate the minimum horizontal stress.

Each data set is randomly divided into 3 parts, including:

- Training data: accounts for 70% of the data set. These values are used during network training.
- Test data: accounts for 15% of the data set. These values are used to test the effectiveness of the network during and after network training.
- Validation data: accounts for 15% of the data set. These values are used to check whether overfitting has occurred or not.

Step 2: ANN models building

In this study, four artificial neural networks models denoted A, B, C and D respectively were built. For each model, the number of hidden layers and the number of neurons of the hidden layers were optimized by trial and error: we started with 1 hidden layer with 1 neuron, then the number of neurons increased after each trial until the least error was acquired. We increased the number of hidden layers to 2 layers and proceeded to determine the network with the least error by increasing the number of neurons in each hidden layer after each trial. Each model has its own input and network structure as follows:

- Model A: Input data for this model is P_P and S_v of the two wells X1 and X2, and output data is minimum horizontal stress of these two wells respectively. Model A has two hidden layers with the numbers of neurons in each layer are 10 and 10. Data set 1 is used for model A.

- Model B: Input data for this model is TVD, P_P and S_v of the two wells X1 and X2, and output data is minimum horizontal stress of these two wells respectively. Model B has two hidden layers with the numbers of neurons in each layer are 9 and 9. Data set 1 is used for model B. Compared with model A, model B added TVD as input data in order to assess the influence of TVD on the minimum horizontal stress estimated result.

- Model C: Input data for this model is TVD, P_P and S_v of the three wells X1, X2 and X3, and output data is minimum horizontal stress of these three wells. Model C has two hidden layers with the numbers of neurons in each layer are 9 and 8. Data set 1 is used for model C. Model C uses input data of three wells, hence one well more than models A and B. This is to assess the effect of the number of wells on the S_{hmin} estimated result.

- Model D: Input data for this model is TVD, P_P and S_v of the three wells X1, X2 and X3, and output data is minimum horizontal stress of these three wells. Model D has two hidden layers with the numbers of neurons in each layer are 9 and 10. Data set 2 is used for model D. Model D uses data set 2 instead of data set 1 to assess the impact of stratigraphic consistency on the estimation.

For reminder, data set 1 and data set 2 were mentioned in **Section 2.2. Fig. 6** shows the structure of artificial neural networks. The number of neurons in each layer of neural networks is summarized in **Table 1**.
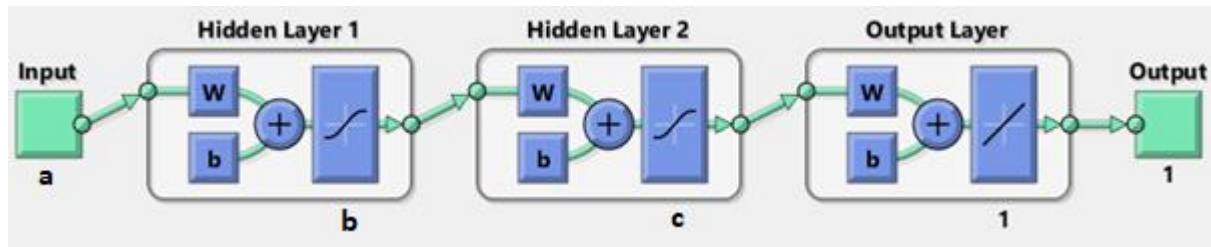

Figure 6 – The perception network for ANN models.

The transfer function of the first and second hidden layers in four mentioned models is hyperbolic tangent sigmoid function because it squashes to a wider numerical range between -1 and 1 and has asymptotic symmetry. On average, it is more likely to create output values that are close to 0, which is beneficial when forward propagating to subsequent layers. The hyperbolic tangent sigmoid function is shown as follow:

$$f(x) = \frac{2}{1 - e^{-2x}} - 1 \tag{2}$$

Step 3: ANN models training, test and validation

Network training is basically the process of adjusting weights and bias. Weight values were taken by default with random values at the start of network training. During the training process, in each epoch, an algorithm is used to adjust the weight values until the desired error of output value is reached. This process increases the ability of the network to predict reliable results when a different set of input data is used.

The results of the network training will be displayed as mean square error (MSE) and regression coefficient (R^2) of the three data sets training, test and validation.

The formulas for calculating MSE and R^2 are given as follows:

$$MSE = \frac{\sum_i^N (y_i - y_i^*)^2}{N} \tag{3}$$

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - y_i^*)^2}{\sum_{i=1}^N (y_i - \bar{y}_i)^2} \tag{4}$$

With: $\bar{y}_i = \frac{1}{N} \sum_{i=1}^N y_i$

Where: y_i: Predictive value;

y^*_i: Real value;

N: Number of samples.

Step 4: Reliability checking

After step 3, the artificial neural networks now must be checked for accuracy and overfitting. The MSE and R^2 values in step 3 will be displayed on a performance plot and regression plots.

An artificial neural network is considered reliable if it achieves the following results:

- Network error, network test and cross-validation are low. In this study, the maximum acceptable error is about 5% of the mean value of the calculated parameter.

- Network training error is stable, which means the error does not vary too much in the last epochs.

- Overfitting is not significant. Overfitting occurs when the MSE of the training error is much smaller than the MSE of the test error.

After making sure the ANN works well with high reliability, the network can then be used for further studies.

Step 5: Application of the models for the well X4 whose minimum horizontal stress need to be estimated.

Specifically, for each model, we have input data as follows:

- Model A: Input data is P_P and S_v of the well X4 in data set 1.
- Model B and model C: Input data is TVD, P_P and S_v of the well X4 in data set 1.
- Model D: Input data is TVD, P_P and S_v of the well X4 in data set 2.

2.4. Estimation workflow of minimum horizontal stress using a combination of artificial neural network and geostatistics

The geostatistical interpolation technique used in the study is Kriging **(Oliver and Webster, 2014)** [12]. Basic equation of Kriging is:

$$Z_{x0} - m_0 = \sum_{i=1}^{n} \lambda_i [Z_{xi} - m_i] \tag{5}$$

Where: Z_{x0}: Estimated value at the observation point x_0;

mo: Mathematical expectation of the function in points x_0;

λ_i: Weight;

Z_{xi}: The known values are near the point to be estimated;

mi: Mathematical expectation of the function in points x_i.

All data used in this section are from data set 2. The steps for building the model combining ANN and geostatistics are detailed as follows:

Step 1: An ANN model named E was built using input data TVD, P_P, S_v of the well X1 and network's target is minimum horizontal stress of this same well X1. Fig. 6 and Table 1 show the structure of the model E.

Table 1 – Number of neurals in layers of ANN models.

Model	Input layer	Hidden layer 1	Hidden layer 2	Output layer
A	2	10	10	1
B	3	9	9	1
C	3	9	8	1
D	3	9	10	1
E	3	9	10	1

Step 2: After the model E was trained, tested and validated in step 1, it was then used for estimating minimum horizontal stress of the wells X2 and X3.

Step 3: Developing a minimum horizontal stress interpolation model (Model I) by Kriging with original data set 2 of the three wells X1, X2, X3. Then, we interpole S_{hmin} of the well X4 by the model I.

Step 4: Developing a minimum horizontal stress interpolation model (Model II) by Kriging with S_{hmin} of the well X1 is taken from the original data set 2 while S_{hmin} of the wells X2 and X3 are generated by ANN model E from step 2. Then, we interpole S_{hmin} of the well X4 by the model II.

Step 5: Analysis the results obtained from model I and model II.

3. Results and Discussion

3.1. Estimation of minimum horizontal stress using artificial neural networks

After the process of network construction, training and reliability test, the ANN training results for models A, B, C and D are presented in **Table 2**, **Table 3**, **Table 4** and **Table 5** respectively. The result tables show the MSE and R^2 values of network training data, validation data and test data. The MSE and R^2 values showed that all models can be considered reliable because they meet the conditions of low training error, low cross-validate error, high regression coefficient and negligible overfitting. Moreover, overfitting does not occur if training errors and test errors are low and stable in the last epochs, which is clearly shown in **Fig. 7**, **Fig. 8**, **Fig. 9** and **Fig. 10** where performance of error values during network training of models A, B, C and D are presented respectively.

Table 2 – Network training of model A.

Data set	Number of samples	MSE x 10^{-5}	R^2
Training	2800	6.8350	0.99993
Validation	600	6.6843	0.99992
Test	600	7.1984	0.99992

Table 3 – Network training of model B.

Data set	Number of samples	MSE x 10^{-7}	R^2
Training	2800	1.4795	1
Validation	600	1.7979	1
Test	600	1.3989	1

Table 4 – Network training of model C.

Data set	Number of samples	MSE x 10^{-7}	R^2
Training	4200	5.9889	1
Validation	900	6.0897	1
Test	900	5.6890	1

Table 5 – Network training of model D.

Data set	Number of samples	MSE x 10^{-9}	R^2
Training	2940	2.0220	1
Validation	630	2.4192	1
Test	630	2.0245	1
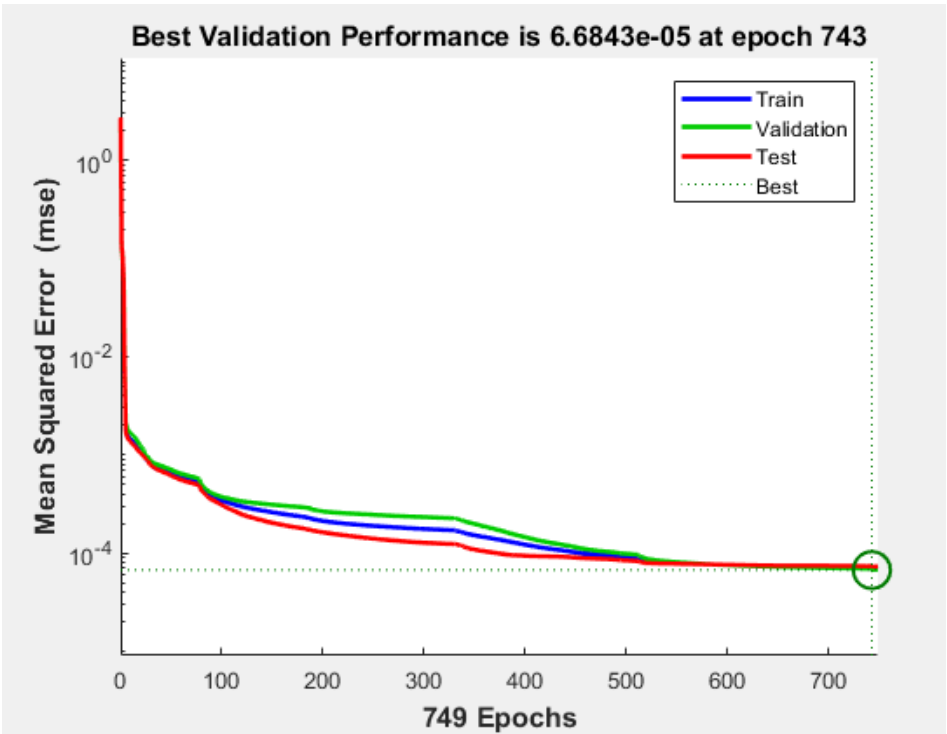
Figure 7 – The mean square error curve versus the number of repetitions performed in the training mode, validation and test for model A.
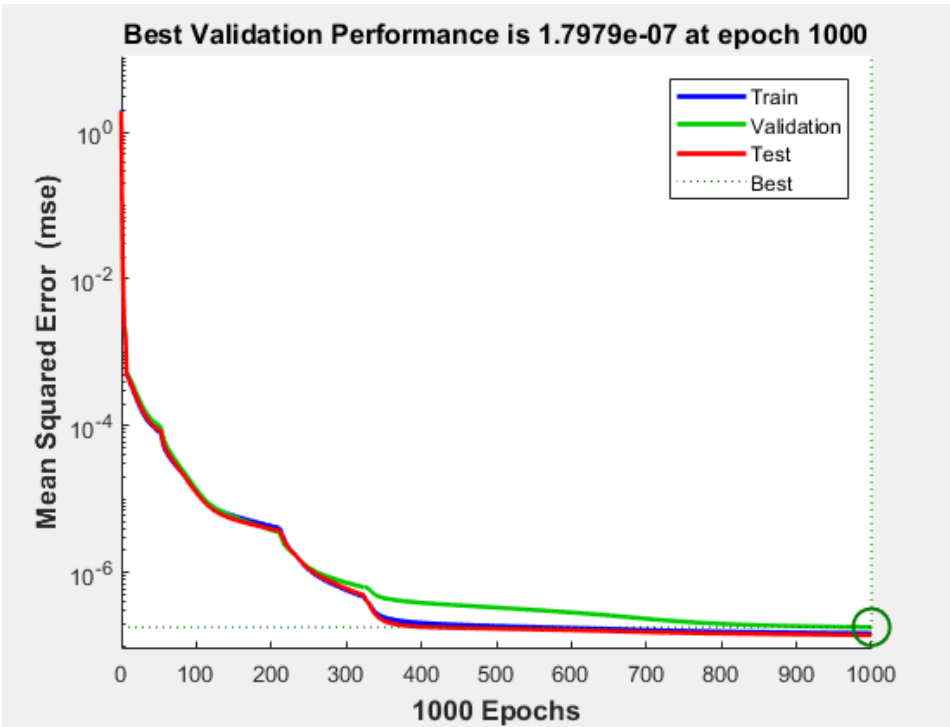
Figure 8 – The mean square error curve versus the number of repetitions performed in the training mode, validation and test for model B.
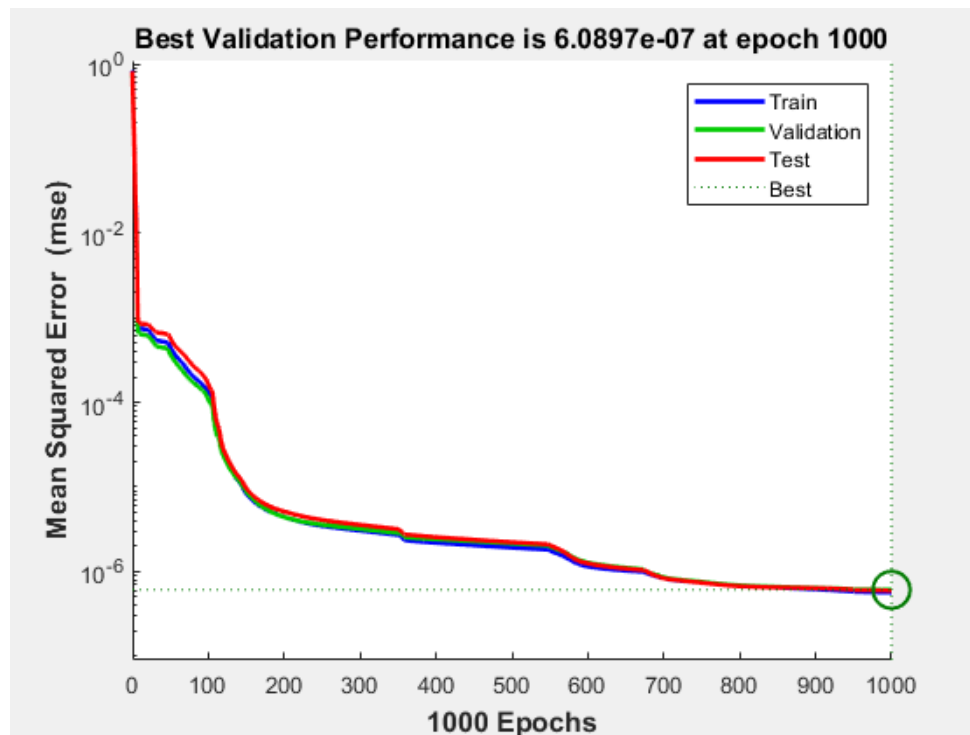
Figure 9 – The mean square error curve versus the number of repetitions performed in the training mode, validation and test for model C.
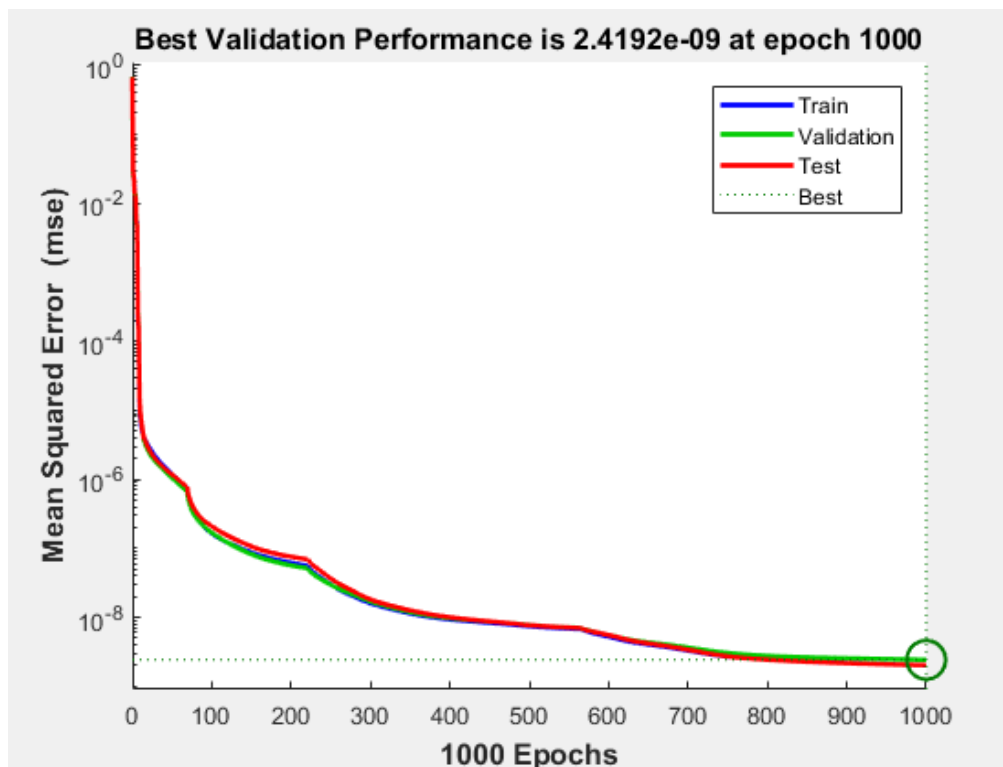

Figure 10 – The mean square error curve versus the number of repetitions performed in the training mode, validation and test for model D.

These models were then used to estimate minimum horizontal stress for the well X4. The values of S_{hmin} of the well X4, which were estimated by the models A, B, C and

D are presented in **Fig. 11**, **Fig. 12**, **Fig. 13** and **Fig. 14** respectively. The results indicated a clear closed correspondence between the predicted and actual data.
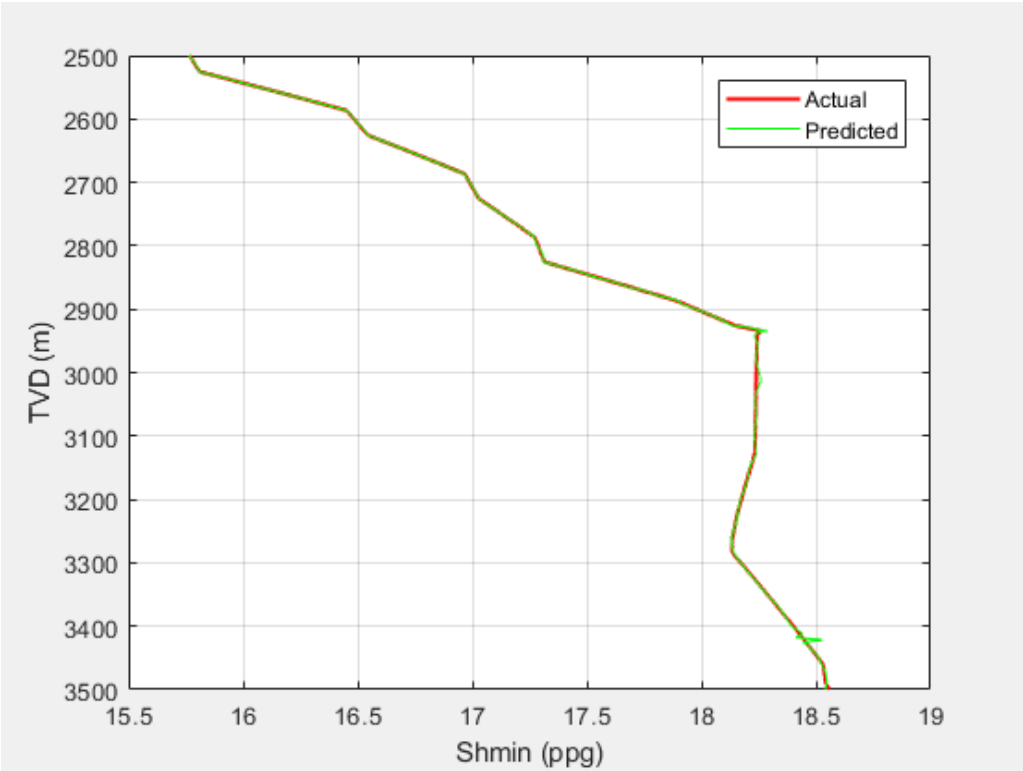

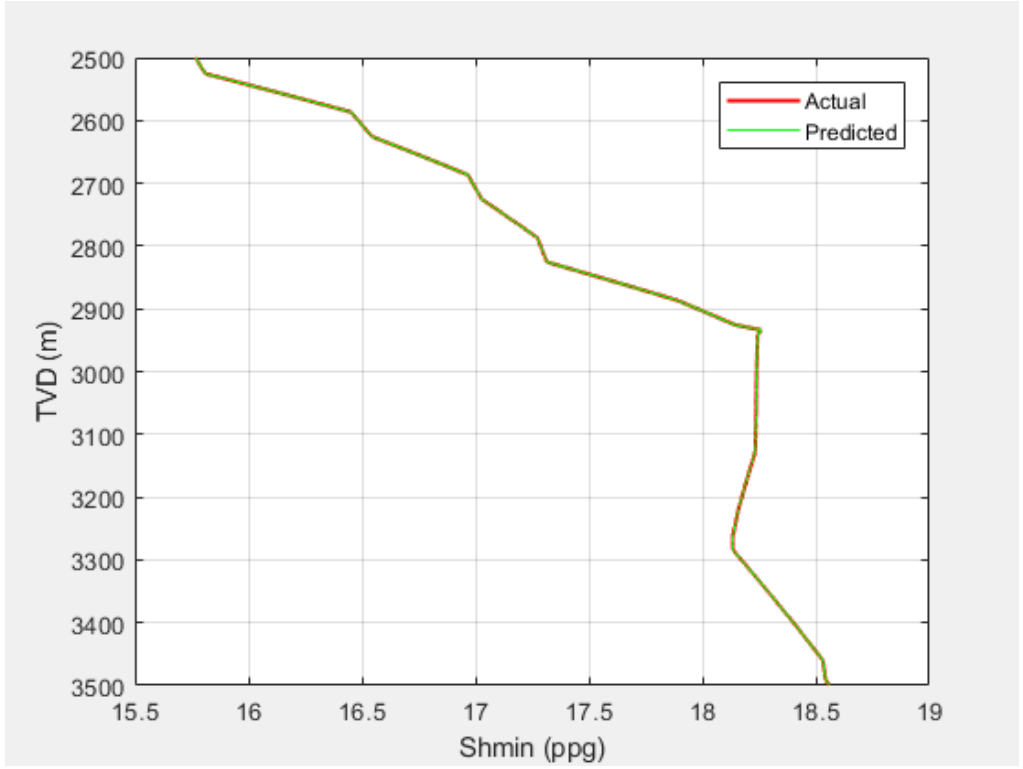**Figure 11** – Minimum horizontal stress of well X4 estimated by model A.

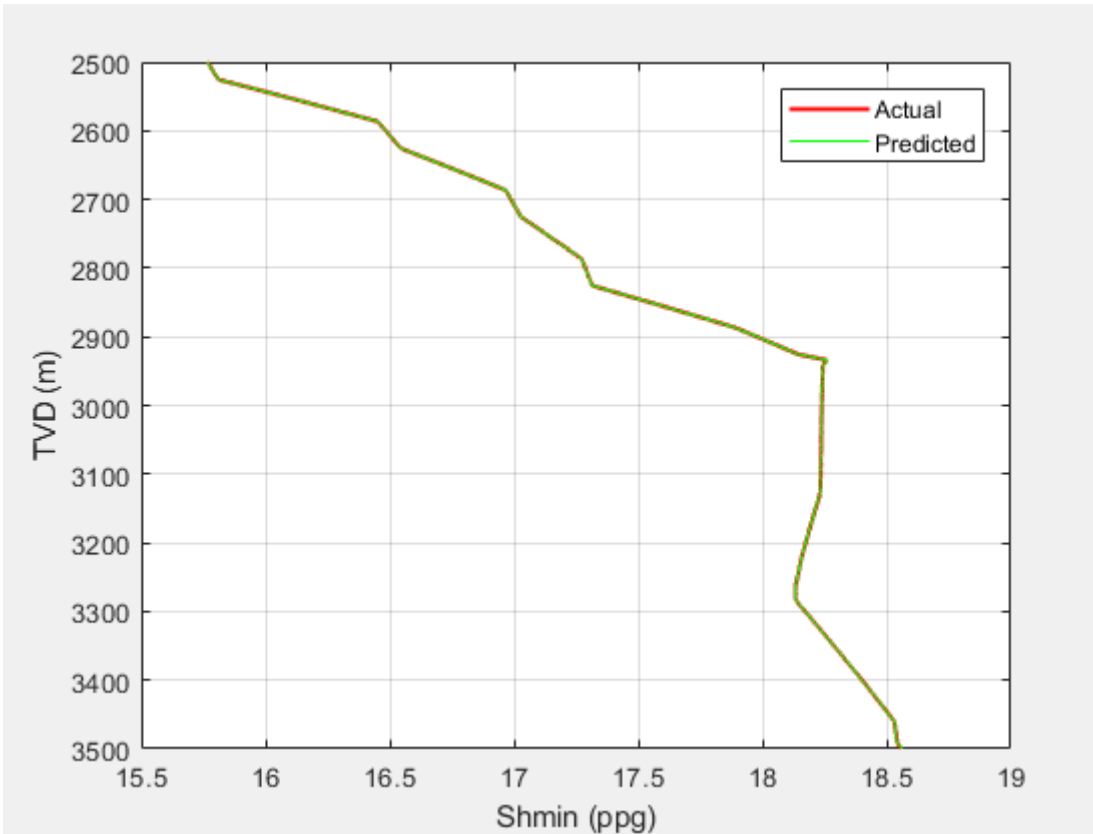**Figure 12** – Minimum horizontal stress of well X4 estimated by model B.

Figure 13 – Minimum horizontal stress of well X4 estimated by model C.
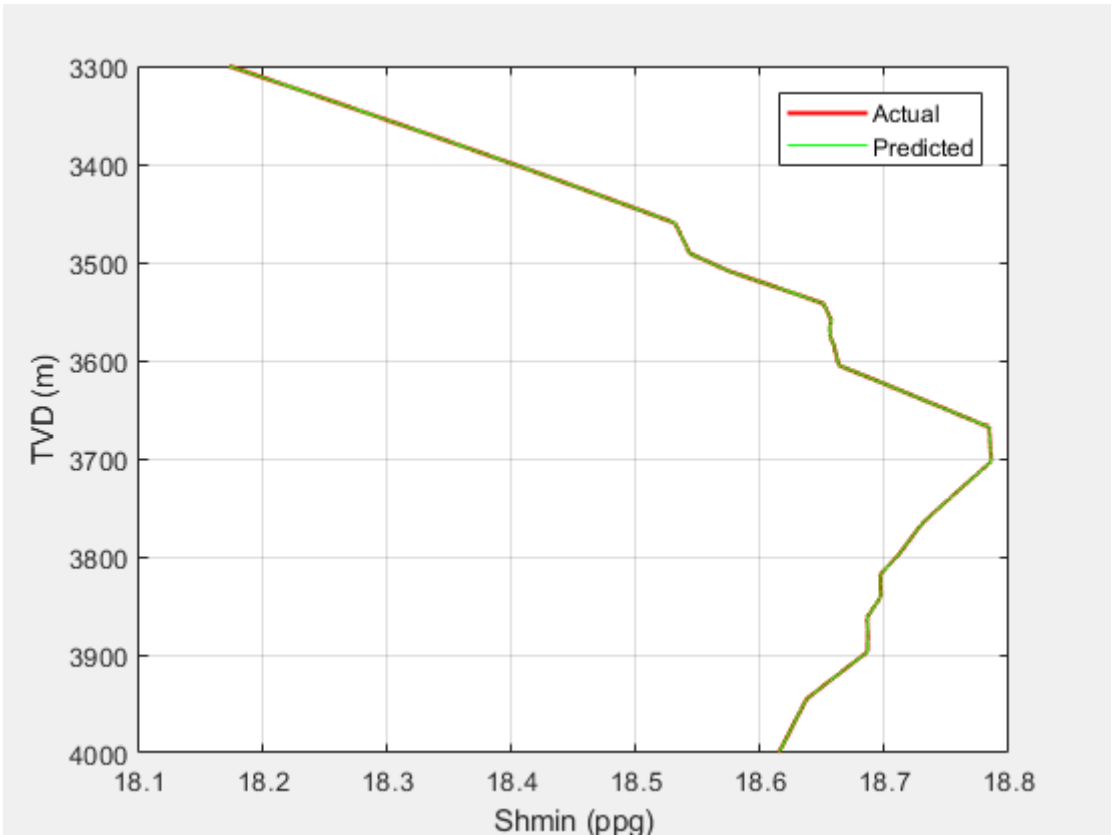

Figure 14 – Minimum horizontal stress of well X4 estimated by model D.

This observation can be confirmed not only visually by Fig. 11, Fig. 12, Fig. 13 and Fig. 14 but also quantitatively by the values of MSE and regression coefficients presented in **Table 6**. Effectively, all models have a value of R^2 equal to 1. In addition, the MSE values of the four models are small. The biggest value of MSE belongs to the case of model A with MSE = 3.5723 x 10^{-5}. With the average value of minimum horizontal stress actually equal to about 18.61 ppg, the absolute error of model A is about 0.0002%, which is totally acceptable. Therefore, other models with smaller MSE obviously have acceptable results.

Table 6 – Accuracy assesing of ANN models.

Model	MSE	R^2
A	3.5723 x 10^{-5}	0.9999
B	1.4680 x 10^{-7}	1
C	4.4934 x 10^{-7}	1
D	1.8952 x 10^{-9}	1

Regarding the influence of TVD, model B has MSE = 1,4680 x 10^{-7} while that of model A is 3.5723 x 10^{-5}. Having the same number of input wells, model B has TVD added to the input data, and the results of MSE show that model B estimates 41.09 times better than model A. Hence, if we can add TVD into input data, the model will give much better estimation of minimum horizontal stress.

Comparing the results of model B and C, model C has an MSE = 4.4934 x 10^{-7}, which is about 3.06 times the MSE result of model B. Hence, it is concluded that adding one

well's data into the input data does not change significantly the MSE results in this case.

Model D has MSE = 1.8952 x 10^{-9}, which is 42.18 times better than model C. The uniformity of stratigraphy therefore greatly affects the results. So, it is better if the data can be divided according to each stratigraphy layer.

3.2.   Estimation of minimum horizontal stress using a combination of Artificial Neural Network and Geostatistics

As mentioned above in **Section 2**, two models I and II were developed with model I conducted purely Kriging interpolation while model II effectuated a combination of ANN and geostatistics. The results of 2D minimum horizontal stress interpolation map and the regression analysis are presented in **Fig. 15** and **Fig. 16** for model I, and in **Fig. 17** and **Fig. 18** for model II respectively. The results of the two models I and II showed no significant difference. Although using only one data well, the method of combining ANN and Kriging did successfully build a interpolation model similar to the one obtained using Kriging method alone which used three data wells.

The MSE and R^2 analysis of the two models I and II is summarized in **Table 7.**

<div align="center">

Table 7 – Accuracy assesing of models I and II.

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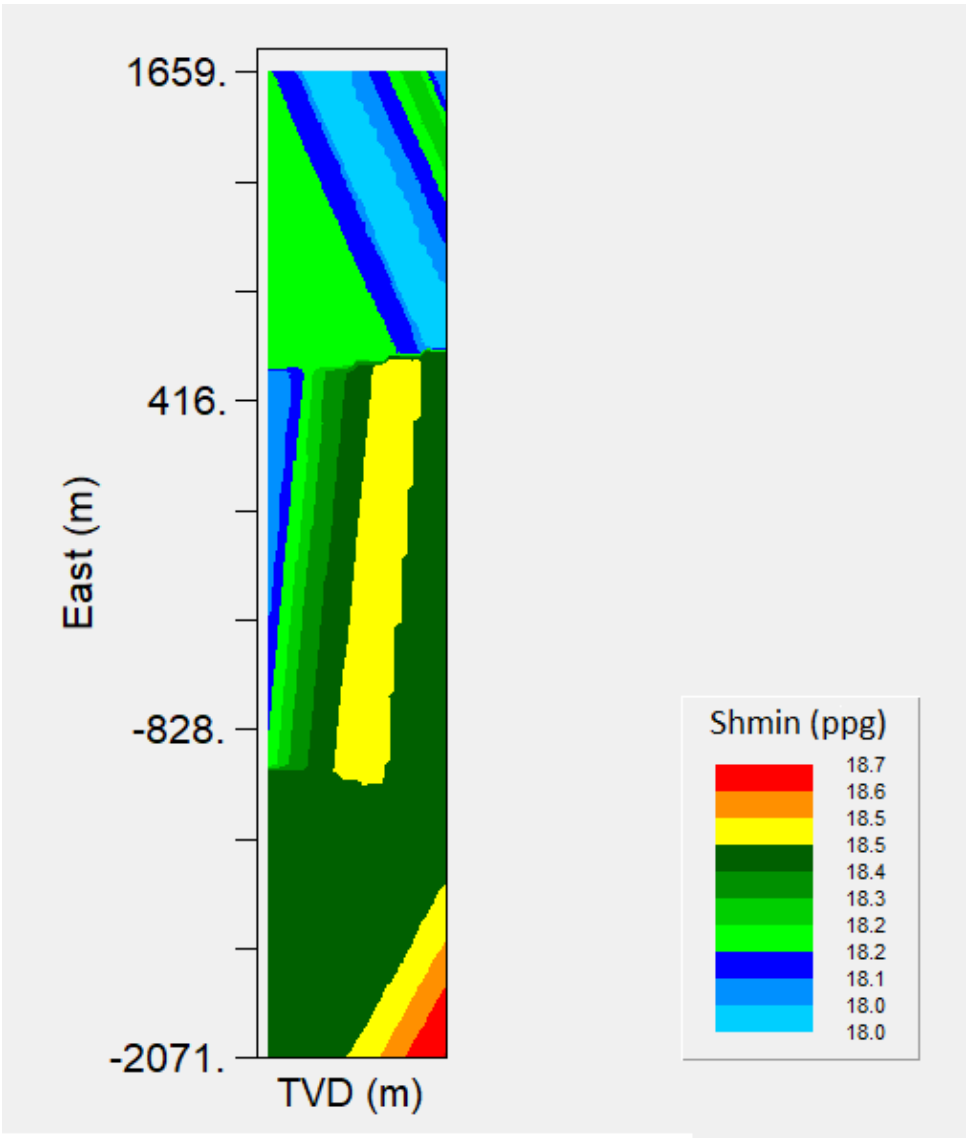| Model	MSE x 10^{-3}	R^2
Model I	5.7150	0.8590
Model II	5.7210	0.8589

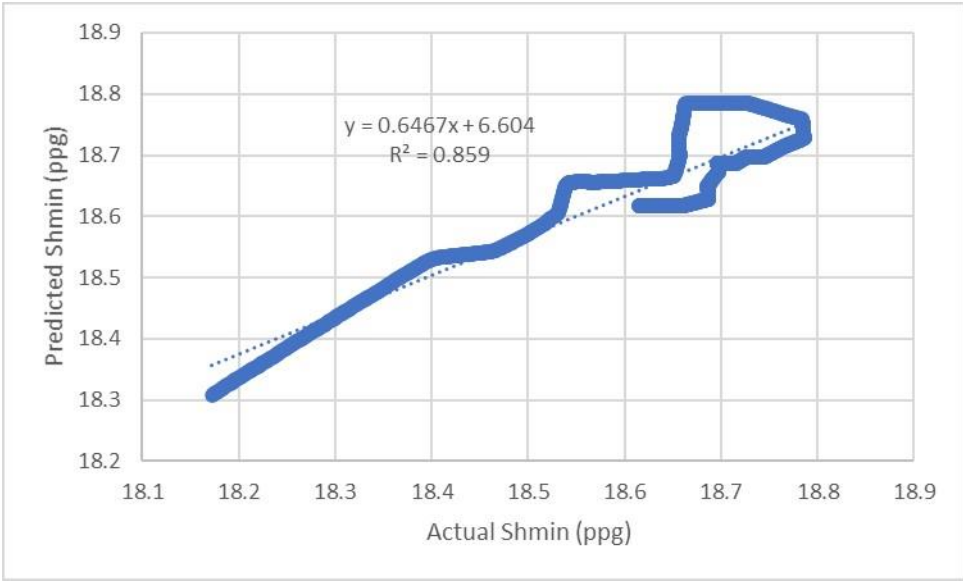**Figure 15 –** Minimum horizontal stress estimated by model I.

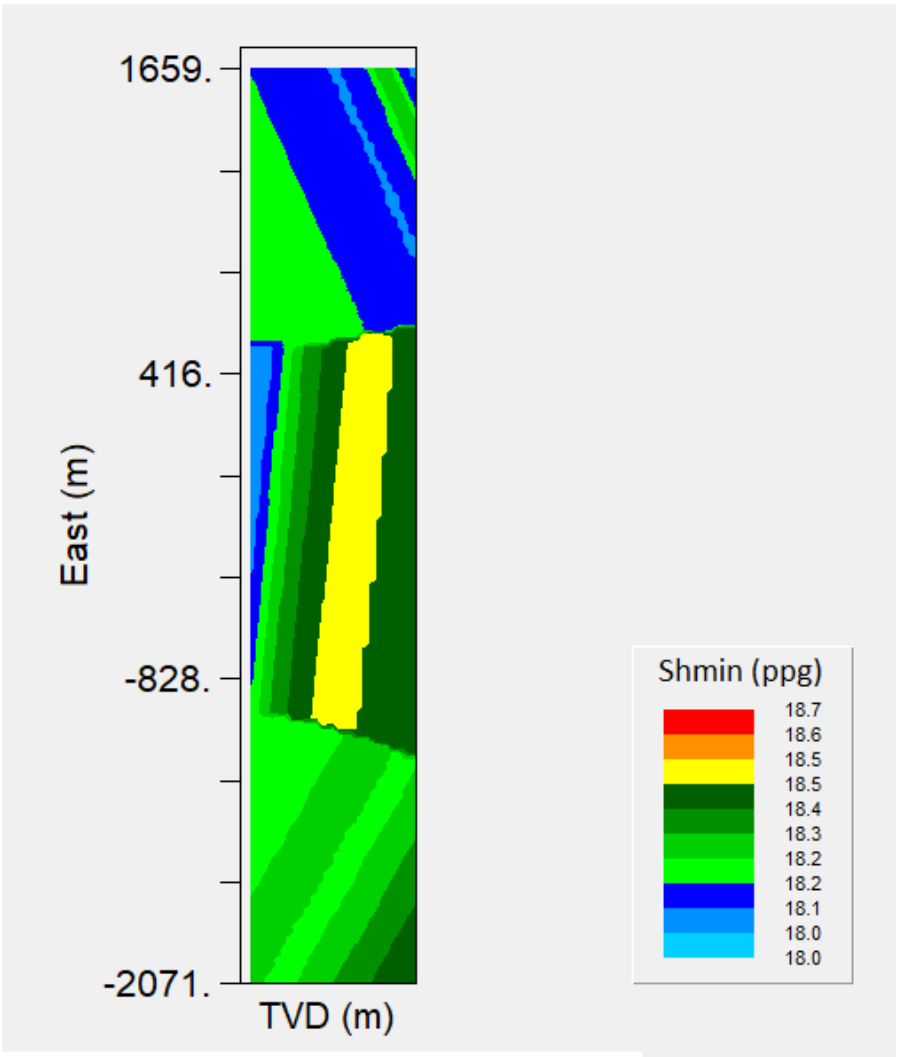**Figure 16 –** Regression analysis for model I.

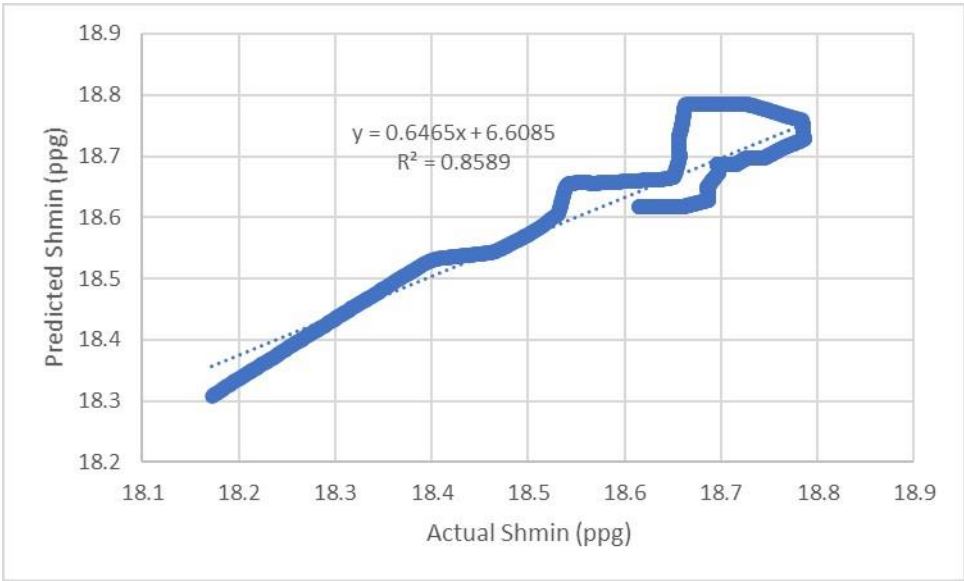**Figure 17 –** Minimum horizontal stress estimated by model II.

Figure 18 – Regression analysis for model II.

These results indicated clearly that the combination of ANN and geostatistics worked well with acceptable estimated values of minimum horizontal stress in comparison with the model that performed geostatistics only. Hence, it is safe to say that using data of only one well to build a model combining ANN and geostatistics can be applied in practice instead of using at least three wells while using just geostatiscal methods. The number of wells with data for modeling does not significantly affect the forecast results. In fact, having a well with the necessary data is not easy. Instead of drilling multiple wells and making measurements to get data, engineers can use the optimal number of wells and build the right models and thereby estimate the required parameters with high accuracy and good performance compared to drilling new wells.

4.   Conclusion

This paper proposed a workflow combining artificial neural networks and geostatistics to build the principal minimum horizontal stress for the four wells of Hai Thach – Moc Tinh field in Nam Con Son Basin. In comparison with geostatistical method which requires at least data of three wells to develop an accurate interpolation model, the proposed method combining ANNs and geostatistics needed only data from one well, which contributes hugely in real life practice as the number of wells with data is often limited and hence without the need to drill additional wells, with this new proposed workflow it is still possible to predict the data of an area with high accuracy.

The authors presented a workflow to build models to estimate minimum horizontal stress from geomechanical parameters through a combination of artificial neural networks and geostatistics. The method of combining ANN and Kriging showed the same result as the traditional Kriging method in spite of using less input data. This research also showed that input data for training ANN models should take depth parameter into account as it increases significantly the accuracy of the results. This is not a practical problem since every logging is recorded within the depth. In addition, the research indicated that the stratification greatly influenced the forecast results. Therefore, the analysis of the initial data by stratigraphy is necessary in the data preprocessing step in this workflow to increase the model's accuracy.

Conflict of interest

On behalf of all the co-authors, the corresponding author states that there is no conflict of interest.

ABBREVIATION

ANN	Artificial Neural Network
LOT	Leak-off Test
MD	Measure Depth
MSE	Mean Square Error
P_P	Pore Pressure
R^2	Regression Coefficient
S_{hmin}	Minimum Horizontal Stress
S_v	Vertical Stress
TVD	True Vertical Depth

REFERENCES

1. Lisa Song. 2012. Measurement of Minimum Horizontal Stress from Logging and Drilling Data in Unconventional Oil and Gas. Doctor of Science thesis, University of Calgary.
2. Jamshidian, M., Zadeh, M. M., Hadian and Nekoeian, M. S. 2016. Estimation of minimum horizontal stress, geomechanical modeling by hybrid neural network based on conventional well logging data – a case study. *Geosystem Engineering*.
3. Dowd, P. A., Saraç, C. 1994. A Neural Network Approach to Geostatistical Simulation. *Mathemetical Geology* **26** (4): 491 – 503.
4. Kanevsky, M., Arutyunyan, R., Bolshov, L. and Demyanov, V. 1996. Artificial Neural Networks and Geostatistics for Environmental Mapping. *Transactions on Information and Communications Technologies*, Vol. 16.
5. Sadun Arzuman. 2009. Comparison of Geostatistics and Artificial Neural Netwoks in Reservoir Property Estimation, Doctor of Philosophy thesis, The Middle East Technical University.

6. Moasheri, S. A., Goshki, A. S. and Parsaie, A. 2013. "SAR" Qualities parameter persistence by a compound method of geostatic and artificial neural network (Case study of Jiroft plain). *International Journal of Agriculture and Crop Sciences* **6** (3): 157 – 166.

7. Hashemi, S., Javaherian, A., Ataee-pour, M. et al. 2014. Channel characterization using multiple-point geostatistics, neural network, and modern analogy: A case study from a carbonate reservoir, southwest Iran. *Journal of Applied Geophysics* **11**: 47 – 58.

8. Soares, S. A. F., Neto, G. S. and Roisenberg, M. 2016. Improving the Incremental Gaussian Mixture Neural Network Model for Spatial Interpolation and Geostatistical Simualation. *International Joint Conference on Neural Networks*: 2507 – 2514.

9. Ríos, R., Ribó, A., Mejía, R. and Molina, G. 2016. Combining Neural Networks and Geostatistics for Landslide Hazard Assessment of San Salvador Metropolitan Area, El Salvador. *Revista De Matemática: Teoría Y Aplicaciones* **23** (1): 155 – 172.

10. Rasouli, V., Pallikathekathil, Z. J. and Mawuli, E. 2011. The influence of perturbed stresses near faults on drilling strategy: A case study in Blacktip field, North Australia. *Journal of Petroleum Science and Engineering* **76**: 37 – 50.

11. Charlez, Ph. A. 1999. The Concept of Mud Weight Window Applied to Complex Drilling. *SPE Annual Technical Conference and Exhibition Houston, Texas,* SPE-56758-MS.

12. Oliver, M. A., and Webster, R. 2014. A tutorial guide to geostatistics: Computing and modelling variograms and kriging. *CATENA* **113**: 56 – 69.

13. Bre, F., Gimenez, J. M. and Fachinotti, V. D. 2018. Prediction of wind pressure coefficients on building surfaces using Artificial Neural Networks. *Energy and Buildings* **158:** 1429 – 1441.