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Using Artificial Neural Networks to Estimate Mud Losses Prior to Drilling for Natural Fractures Formations

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Abstract

Lost circulation is a complicated problem to be predicted with conventional statistical tools. As drilling environment is getting more complicated nowadays, more advanced techniques such as artificial neural networks (ANNs) are required to help to estimate mud losses prior to drilling. The aim of this work is to estimate mud losses for natural fractures formations prior to drilling to assist the drilling personnel in preparing remedies for this problem prior to entering the losses zone. Once the severity of losses is known, the key drilling parameters can be adjusted to avoid or at least mitigate losses as a proactive approach. Lost circulation data were extracted from over 2000 wells drilled worldwide. The data were divided into three sets; training, validation, and testing datasets. 60% of the data were used for training, 20% for validation, and 20% for testing. Any ANN consists of the following layers, the input layer, hidden layer(s), and the output layer. A determination of the optimum number of hidden layers and the number of neurons in each hidden layer is required to have the best estimation, this is done using the mean square of error (MSE). A supervised ANNs was created for natural fractures formations. A decision was made to have one hidden layer in the network with ten neurons in the hidden layer. Since there are many training algorithms to choose from, it was necessary to choose the best algorithm for this specific dataset. Eight different training algorithms were tested, the Levenberg-Marquardt (LM) algorithm was chosen since it gave the lowest MSE and it had the highest R-squared. The final results showed that the supervised ANN has the ability to predict lost circulation with an overall R-squared of 0.925 for natural fractures formations. This is a very good estimation that will help the drilling personnel prepare remedies before entering the losses zone as well as adjusting the key drilling parameters to avoid or at least mitigate losses as a proactive approach. This ANN can be used globally for any natural fractures formations that are suffering from the lost circulation problem to estimate mud losses. As the demand for energy increases, the drilling process is becoming more challenging. Thus, more advanced tools such as ANNs are required to better tackle these problems. The ANN created in this paper can be adapted to commercial software that predicts lost circulation for any natural fractures formations globally.

Introduction

An artificial neural network is "an information-processing system that has certain performance characteristics in common with biological neural network" (Mohaghegh, 2000). All organisms are made up of cells. Neurons are the basic building blocks of the nervous system. A typical biological neuron consists of a cell body, an axon, and dendrites. Information in the cell body enters through the dendrites. The cell body then provides an output which travels through the axon then to another receiving neuron, the output from the first neuron becomes an input for the second neuron and so on (Mohaghegh, 2000).

Figure A.1 (Appendix A) is a schematic of an artificial neuron, the outputs from other neurons are multiplied by the connection links weights and enter the neuron. The inputs then are summed and the activation function of the neuron is applied which leads to an output. Thus, a neuron has multiple inputs and only one output. An artificial neural network consists of one input layer, one or more hidden layers, and one output layer. The input and output layers are obviously for inputs and outputs. The hidden layer is responsible for extraction the features from the data (Mohaghegh, 2000). ANNs can be simple three layers as shown in **Figure A.2** (Appendix A), or ANNs can be more complicated as shown in **Figure A.3** (Appendix A).

ANNs have been utilized in exploration, drilling, production, and reservoir engineering applications for a long time. Alkinani et al. (2019b) summarized the applications of ANNs in the petroleum literature.

Drilling fluid losses and problems associated with lost circulation while drilling represent a major expense in drilling oil and gas wells, by industry estimates, more than 2 billion dollars is spent to combat and mitigate this problem each year (Arshad et al., 2015; Alkinani et al., 2019a; Alkinani et al., 2018a). Lost circulation estimation is a limited topic in the literature, only a few papers were published about this topic. Some shortcomings were identified in the literature as follows (Al-Hameedi et al., 2017a; Al-Hameedi et al., 2017b; Al-Hameedi et al., 2018a; Al-Hameedi et al., 2018b; Leite Cristofaro et al., 2017; Li et al., 2018):

1. Not enough data were used.

2. The model is applicable only in a specific area.
3. The methodologies in some papers were not explained very well.

The purpose of this paper is to create an ANN to estimate mud losses prior to drilling natural fractures formations using data of more than 2000 wells (10,000 data points) drilled worldwide. Also, this paper will eliminate the shortcoming mentioned earlier by using huge data sets, the model will be applicable globally since the data were collected globally, and the methodology will be explained in details.

Methodology for Creating the Neural Network

In this section, various steps for creating the feedforward backpropagation networks for natural fractures formations will be shown.

Data Collection, Data Processing, and Input Data Selection

Data collection is the most time-consuming step of this work. Key drilling parameters at the time of mud losses were collected from various sources worldwide including daily drilling reports (DDR), technical reports, mud logging reports, final drilling reports, case histories, and from the petroleum literature. Then, the data of each key drilling parameter were tested for outliers using box plot, such that any data point falls outside the minimum and the maximum of the interquartile range (IQR) will be eliminated (Alkinani et al., 2018b).

After finishing the data preprocessing step (identifying the outliers), the key drilling parameters that will be used as inputs for the model should be chosen. Inputs can be chosen based on experimental tests, modeling, simulation, sensitivity analysis, experts' opinions, statistical analysis and etc. The following inputs were chosen based on two criteria which are statistical and sensitivity analyses done by Al-Hameedi et al. (2017a and 2018a), and experts' opinions:

1. Mud weight (MW) in gm/cc
2. Equivalent circulation density (ECD) in gm/cc.
3. Plastic viscosity (PV) in cp.
4. Yield point (Yp) in Ib/100ft$^{2.}$
5. Flow rate (Q) in L/min.
6. Revolutions per minute (RPM).
7. Weight on bit (WOB) in Tons.
8. Nozzles total flow area (TFA) in inch2

Data Normalization

Sometimes, if the input or the output data are too small, too large or non-normally distributed; therefore, scaling of the data should be performed (Saeedi et al., 2007; Zabihi et al., 2011). One method of normalizing data to have values between -1 and 1 is shown in Equation 1 (Demuth et al., 2007).

$$\mathbf{X_i'} = \mathbf{2}\left[\frac{\mathbf{X_i - X_{min}}}{\mathbf{X_{max} - X_{min}}}\right] - \mathbf{1} \ \ldots \ \textit{(Eq. 1)}$$

Where X_i is the original value of the parameter, X_i' is the normalized value of X_i, X_{max} and X_{min} are the maximum and the minimum values of X_i, respectively.

Choosing the Transfer Function

The tan-sigmoid transfer function was chosen for the hidden layer, and a linear transfer function was used for the outputs layer. Using this combination will allow the network to capture the nonlinear relationship between the inputs and the outputs. The linear transfer function was chosen for the output layer since it is suitable for fitting problems (regression) (Demuth et al., 2007).

Dividing the Data and Feedforward Backpropagation Algorithm

Typically, data are divided into three sections; training, verification, testing sets. The training data used to develop the ANN model, the desired output is used to help the network adjust the weights of each input. The error will backpropagate in the network and adjust the weights until calibration is reached, this method is called the feedforward backpropagation algorithm. It should be noted that the network should not be overstrained since the network will lose its ability to generalize. Verification set (data not used to create the network) is used to measure the network generalization, and to stop the training when generalization stops improving. Testing set (also data not used to create the network) used to test the accuracy of the network after the training and the verification steps.

Since huge data were available, 60% of the data were used for training, 20% used for verification, and 20% for testing. Thus, only 60% of the data used to train the model, the rest used for generalization and testing.

Choosing the Optimum Number of Hidden Layers and Number of Neurons

The optimum number of hidden layers, as well as the number of neurons in the hidden layer, were chosen based on an iterative process. A various number of hidden layers and number of neurons were tested, the goal was to create a network that has the lowest mean squared error (MSE) which is the average squared error between the network estimate outputs (a) and the real output (t). MSE can be calculated using Equation 2 (Demuth et al., 2007).

$$\mathbf{MSE} = \frac{\mathbf{1}}{\mathbf{N}}\sum_{\mathbf{i=1}}^{\mathbf{N}}(\mathbf{t_i} - \mathbf{a_i})^{\mathbf{2}} \ \ldots \ \textit{(Eq. 2)}$$

Where N is the number of data points. The same process was implemented to choose the optimum number of neurons in the hidden layers such that starting with one neuron and then increase the number of neurons until reaching the lowest MSE.

Examination of the Training Function

This is a very pivotal step in creating the network. There are many algorithms available to choose from. **Table A.1** (Appendix A) summarizes the algorithms examined in this study (more information about each algorithm can be found in Demuth et al. (2007)). After testing all algorithms, the lowest MSE with the highest R-squared algorithm was chosen to train the network. R-squared can be calculated using the following Equation:

$$\boldsymbol{R^2 = \frac{SSR}{SST} = \frac{\sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \quad \textbf{\textit{… (Eq. 3)}}$$

Where SSR is the regression sum of squares, SST is the total sum of squares, $\hat{y}_i$ is the predicted data point, $\bar{y}$ is the average mean of the real data, and y_i is the real data point.

Results and Discussion

ANN with one input layer, one hidden layer with ten neurons, and one output layer was created for the natural fractures dataset. **Figures A.4** and **A.5** (Appendix A) show the MSE and R-squared for all training functions examined in this study, respectively. It is clear that LM and BR algorithms have the lowest MSE and R-squared among the other algorithms with the LM algorithm being slightly better than the BR algorithm (LM has lower MSE and higher R-squared). BR algorithm is usually used for small or noisy datasets. Typical BR algorithm doesn't use validation to stop the network when a generalization is reached so that the training can continue until an optimal combination of error and weights is found. On the other hand, LM usually has the fastest convergence which gives accurate training. Also, the LM performs very well in approximation (regression) problems. Training will stop in the LM algorithm when generalization stops improving. Thus, the LM algorithm was chosen to train the network (Demuth et al., 2007).

Figure A.6 (Appendix A) shows the MSE with iterations for training, validation, and testing sets. To avoid overfitting, the MSE in the validation set is monitored and the training will stop once the lowest MSE is reached. Also, the testing and validation MSE should have similar characteristics in order to avoid overfitting and have a rigorous network. **Figure A.6** (Appendix A) shows training stops after 33 iterations which when the MSE for the validation set is minimum. Moreover, **Figure A.6** (Appendix A) clearly shows that the testing and validation sets have the same MSE characteristics.

Figure A.7 (Appendix A) shows the actual and predicted mud losses for training **(Figure A.7a)**, validation **(Figure A.7b)**, testing **(Figure A.7c)**, and all **(Figure A.7d)** datasets. The R-squared for the training, validation, and testing is 0.96, 0.95, and 0.948, respectively. The network has an overall R-squared of 0.956. With this high R-squared, the network can be used to predict mud losses prior to drilling for natural fractures formations.

Equation 4 can be used to estimate mud losses for natural fractures formations prior to drilling.

$$\boldsymbol{Losses = \left[\sum_{i=1}^{N} w_{2i}\left(\frac{2}{1+e^{-2\left(\sum_{j=1}^{J} w_{1i,j}x_j + b_{1i}\right)}} - 1\right) + b_2\right]} \quad \textbf{\textit{… (Eq. 4)}}$$

Where N is the number of neurons in the hidden layer which was optimized to be ten, w_1 is the weight of the hidden layer, w_2 is the weight of the output layer, b_1 is the bias of the hidden layer, b_2 is the bias of the output layer, and x is the input variable. The j is associated with the input variables such that j=1 is MW, j=2 is ECD, j=3 is PV, j=4 is Yp, j=5 is Q, j=6 is RPM, j=7 is WOB, and j=8 is Nozzles TFA. **Table A.2** (Appendix A) summarizes the coefficients for Equation 4.

Conclusions

Lost circulation is a complicated problem to be predicted with conventional statistical tools. As the drilling environment is getting more complicated nowadays, more advanced techniques such as artificial neural networks (ANNs) are required to help to estimate mud losses prior to drilling. Huge data of key drilling parameters at the time of mud losses were collected worldwide for natural fractures formations. The goal was to create an ANN that can be used to predict lost circulation prior to drilling for natural fractures formations. Based on this study, the following conclusions were made:

- A supervised ANN was created to be used to predict lost circulation prior to drilling for natural fractures formations. The networks showed the ability to predict lost circulations prior to drilling within an acceptable range of error.
- After testing a various number of training algorithms, the LM algorithm was chosen to be used since it had the lowest MSE and the highest R-squared which makes it a better predictive model.
- The network developed in this study can be used to estimate the expected amount of the mud losses prior to drilling any natural fractures formations. Alternatively, given a target loss volume, the network can be used in reverse, to set key drilling parameters to limit losses while drilling.
- This study overcame the shortcoming in the previous studies about the estimation of mud losses prior to drilling. This is the first study that provides a generalized model to estimate lost circulation prior to drilling that can be used worldwide.

Acknowledgments

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Appendix A

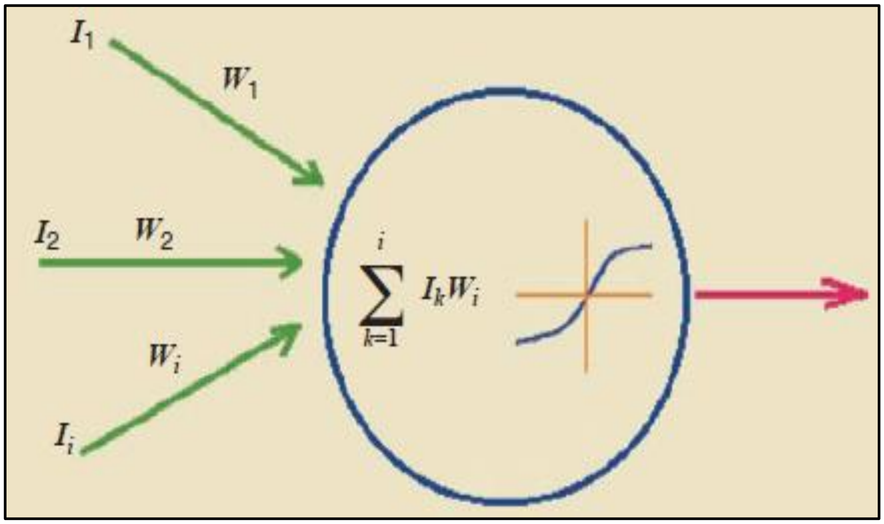

Figure A.1. Schematic of Artificial Neuron (Mohaghegh, 2000)

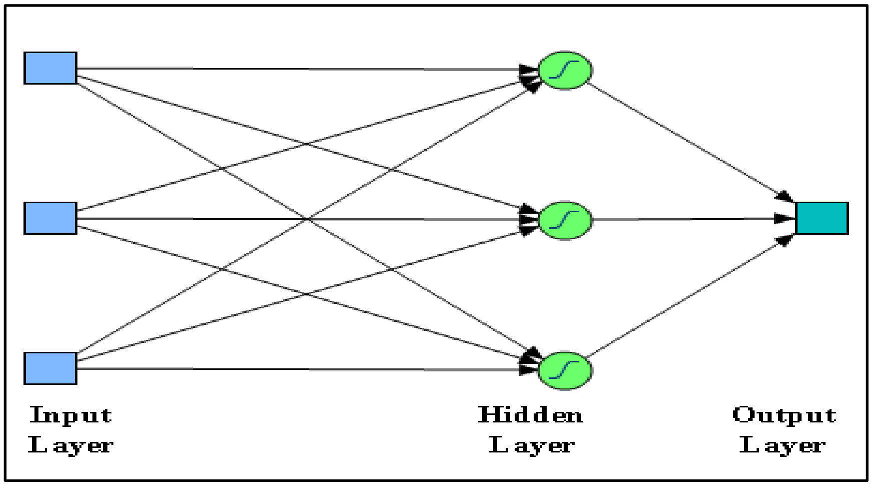

Figure A.2. Example of a Simple Neural Network

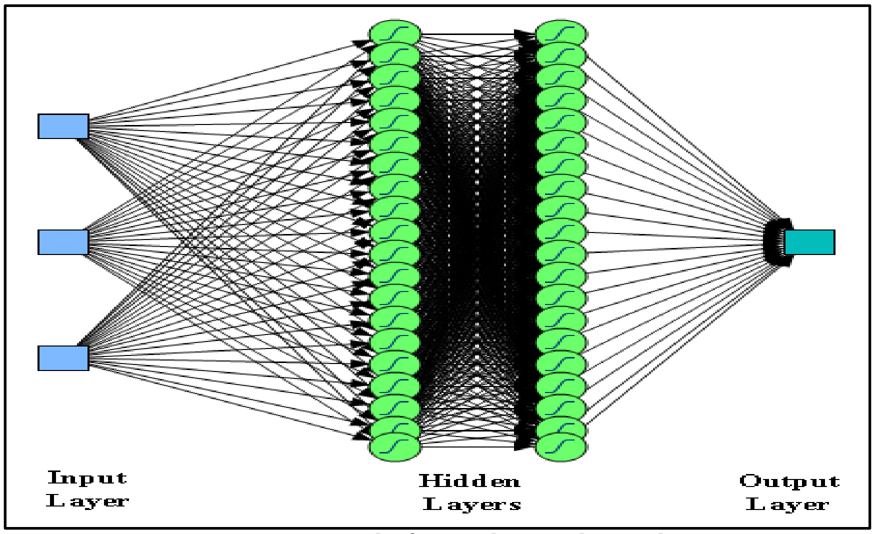

Figure A.3. Example of a Complex Neural Network

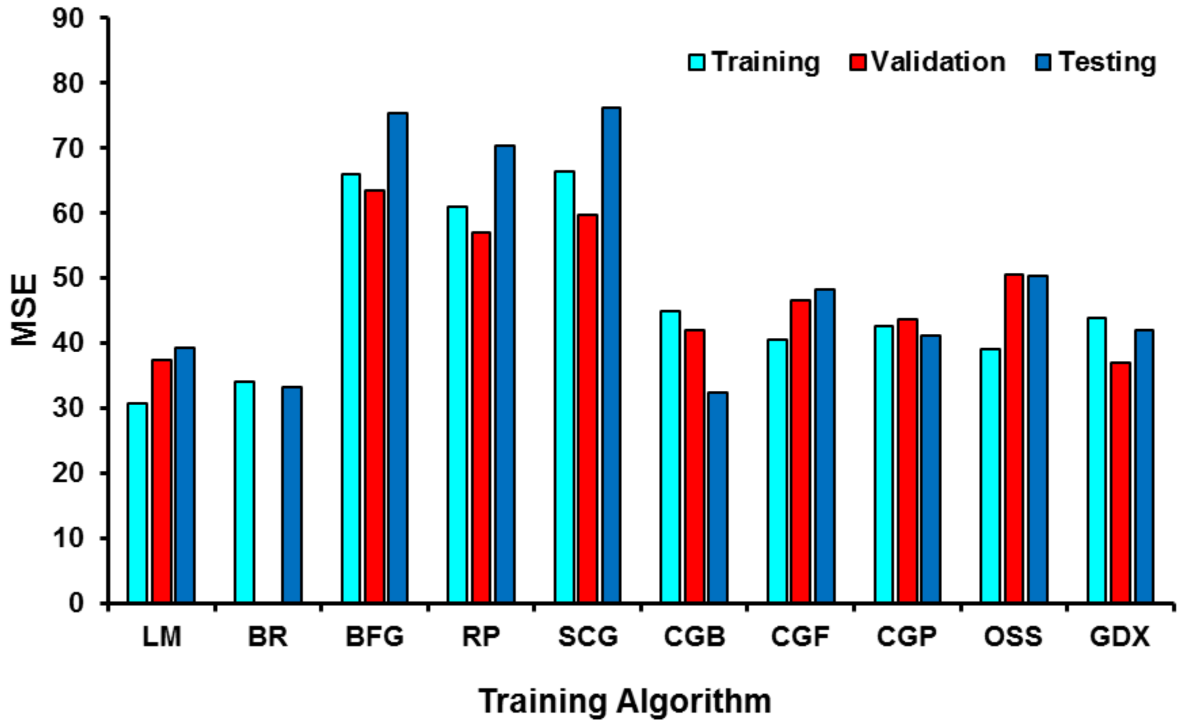

Figure A.4. MSE of all Training Functions Examined in this Study

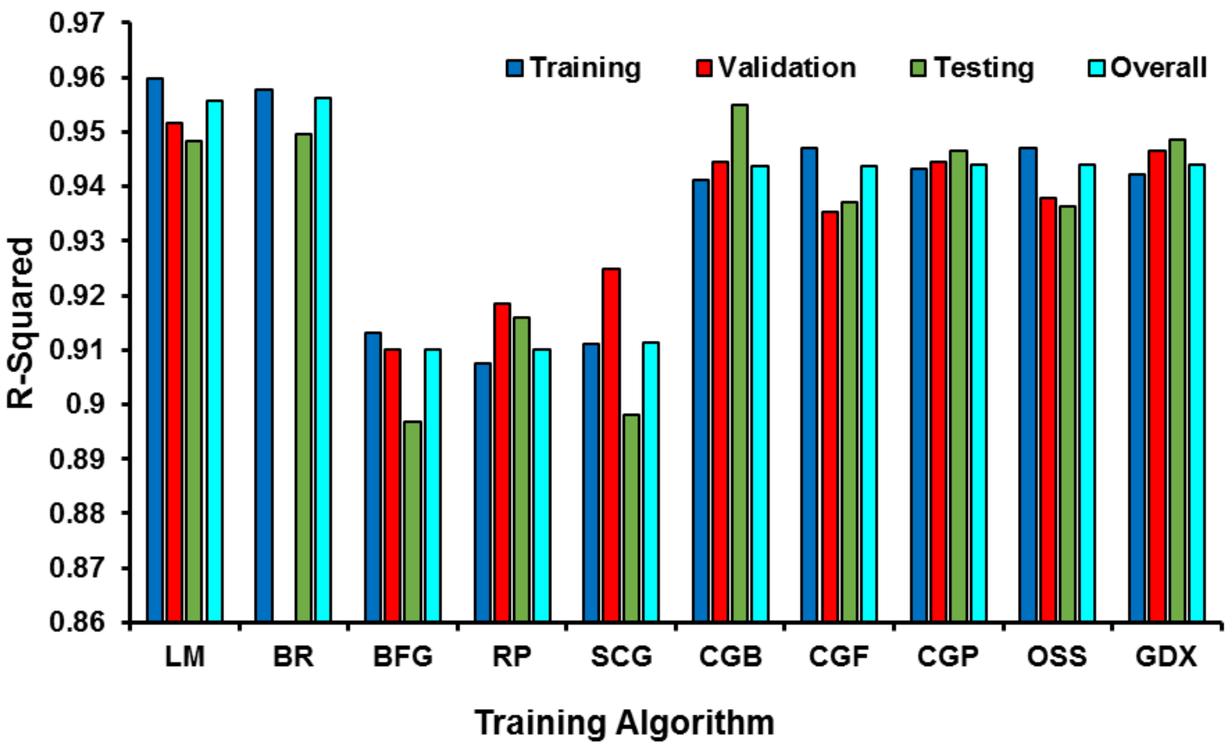

Figure A.5. R-squared of all Training Functions Examined in this Study

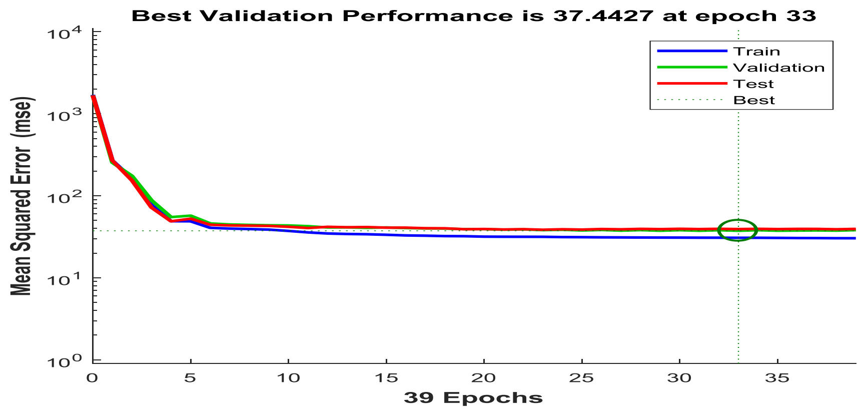

Figure A.6. MSE vs Epochs for the LM Training Function

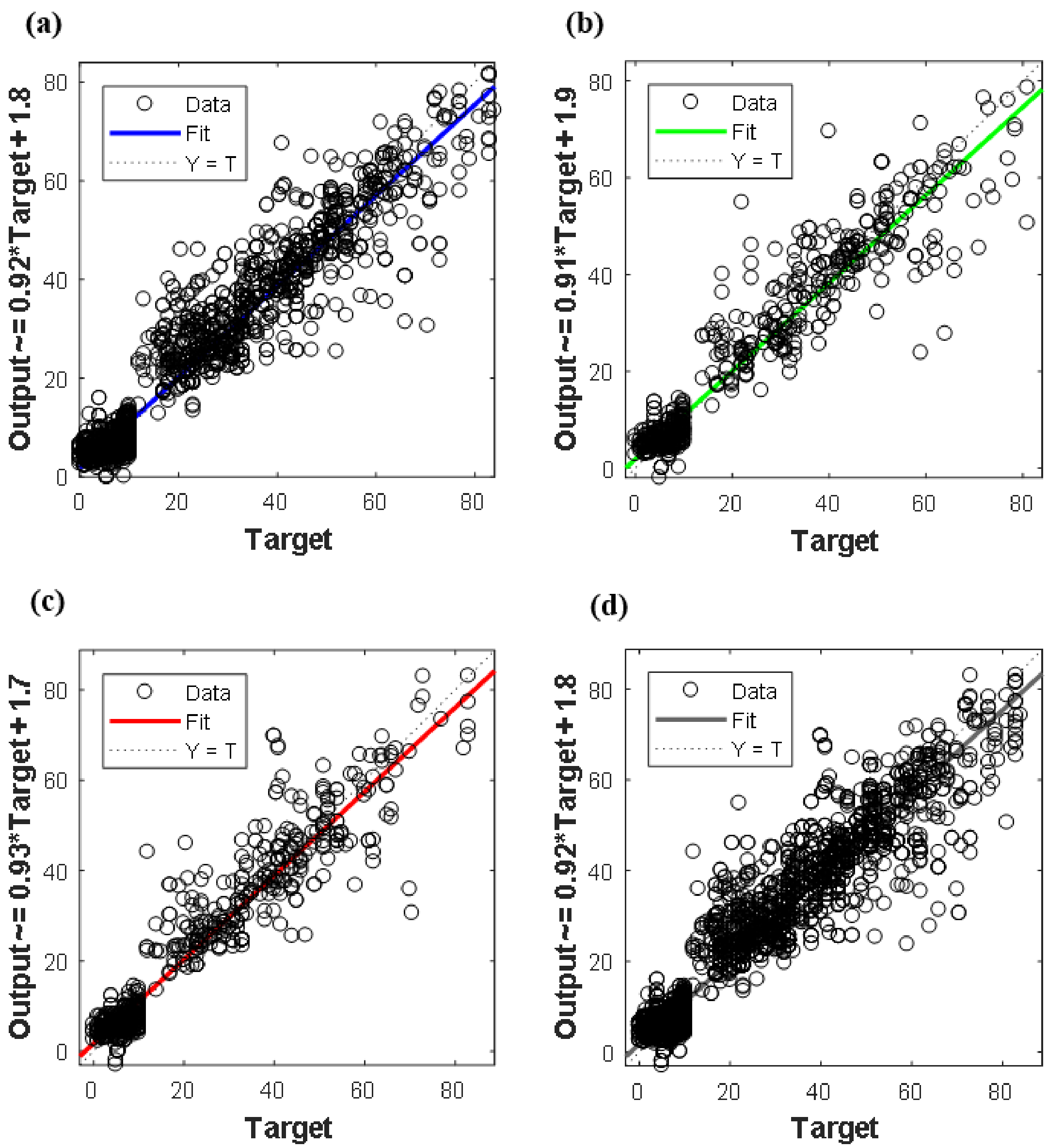

Figure A.7. Predicted and Actual Mud Losses for Training (a), Validation (b), Testing (c), and All (d) Datasets

Table A.1. The Algorithms Examined in This Study

Algorithm	Abbreviations
Levenberg-Marquardt	LM
Bayesian Regularization	BR
Quasi-Newton	BFG
Resilient Backpropagation	RP
Scaled Conjugate Gradient	SCG
Conjugate Gradient with Powell/Beale Restarts	CGB
Fletcher-Powell Conjugate Gradient	CGF
Polak-Ribiére Conjugate Gradient	CGP
One Step Secant	OSS
Variable Learning Rate Backpropagation	GDX

Table A.1. Coefficients for Natural Fracture Formations Mud Losses (Eq. (4))

Hidden Layer Weight Matrix w_{1j}								Hidden Layer Bias	Output Layer Weight Matrix	Output Layer Bias
j=1	j=2	j=3	j=4	j=5	j=6	j=7	j=8	b_1	w_2	b_2
-2.2091	2.7249	1.8762	0.6220	-0.0617	-1.7078	-0.7524	-1.0397	-1.7124	0.3750	-0.2793
-6.9222	3.2221	2.1353	-1.7348	1.1825	-0.8590	0.6850	2.7215	3.5206	-0.2016	
-0.4195	-0.7027	-4.4217	1.4298	-1.3663	0.2557	4.9967	1.8083	4.1717	0.2147	
5.5710	1.4180	2.3832	0.8779	-0.7672	-0.1834	-1.0082	-0.0979	-4.8003	0.3362	
-2.3232	-3.2751	1.3330	0.5541	-1.0229	0.9844	-0.6204	-2.8423	-0.5922	2.4752	
1.0026	0.1431	-0.1428	1.4370	0.2717	-1.6094	-0.3796	-1.6778	-2.2784	-0.7235	
1.2600	1.0021	2.5369	-0.1617	5.4880	-0.4228	4.0073	-3.1335	-3.9646	0.1092	
3.2746	3.3977	-2.1981	-0.7570	1.8079	-1.2094	1.2321	3.5979	0.6624	1.8705	
3.3066	0.7451	-0.1552	-0.1148	-0.1447	0.5618	0.3344	-0.0443	2.1266	0.6306	
2.3620	-3.3680	-0.4873	-1.0335	-0.3052	1.7558	-1.8901	1.1824	3.5360	-0.5589	