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# A New Artificial Neural Network Model to Predict Cutting Transport Efficiency in Deviated and Horizontal Oil Wells

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## ABSTRACT

*Inadequate hole cleaning significantly impacts drilling operations. For example, poor wellbore cleaning can result in various drilling issues, including a reduced rate of penetration (ROP), early bit wear, and, in extreme situations, well loss due to stuck pipe. Numerous studies have been carried out to comprehend how to reduce transport efficiency and offer potential remedies for the issue. They frequently provide empirical correlations based on experimental data. Many engineering fields have recently adopted artificial intelligence and machine learning. Consequently, oil and gas companies have increasingly used artificial neural networks (ANN) to forecast a number of crucial metrics. The purpose of this study is to use artificial intelligence approaches to forecast hole-cleaning efficiency. Two layers, TANSIG and LOGSIG transfer functions, and several training functions were used to construct feed-forward backpropagation ANN models. A dataset of 1,620 experimental records served as the basis for the investigation. Cutting density and pressure losses are included in the input parameters. Additionally, the model input consisted of drilling characteristics such as the drill pipe rotating speed (RPM), flow rate (GPM), pipe, and hole inclination angle. The best-performing model was selected using a sensitivity analysis using 2, 4, 6, and 10 neurons for each transfer function (LOGSIG and TANSIG). With a correlation coefficient (R) greater than 0.9, the results showed that the constructed model accurately predicted the cutting transport efficiency (TE) in the wellbore. The findings demonstrated that as the number of neurons increases, the model's accuracy in terms of R for training and testing also increases. The expected and real TE utilizing the TANSIG transfer function, GDM versus GD learning function, and four different training functions indicate that using the GDM adaption learning function generally outperforms the GD function. For instance, the correlation coefficient (R) for 10 neurons using the GDM function was 97.45 compared to 97.08 for the GD function. Additionally, results indicate that the LOGSIG transfer function a bit overperforms the results estimated by the TANSIG function at two and four neurons. However, at higher numbers of neurons, the TANSIG function performs better. Therefore, it is recommended that using the TANSIG transfer function with the GDM be used for future predictions of transport efficiency (TE).*

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## 1. Introduction

Directional and horizontal wells have proven to be effective field development techniques, satisfying the need for enhanced oil recovery and reducing the overall cost of drilling operations [1]. Cuttings generated during drilling are typically removed from the wellbore using drilling mud. Flow rate [2],[3],[4], fluid properties [5],[6], solid characteristics [7], and the interactions between these parameters are the main factors controlling cutting removal. For instance, Tomren et al. [2] experimentally observed the forming of a cutting bed at low flow rates for wellbore inclinations between 10° and 30°. In addition, a higher tendency of cuttings build-up as wellbore inclination increased. Cho et al. [3] and Ravi and Hemphill [8] reported that the cutting height tends to be minimized by maximizing the flow rate.

To date, downhole drilling technologies have advanced significantly [9]. However, there has been limited research on optimizing hydraulic settings and drilling operations. Therefore, to increase drilling efficiency and reduce costs, the industry needs innovative techniques and approaches to help rig-site staff make decisions on drilling parameters in real-time [1],[11],[12]. It is common practice to plan new wells utilizing data from existing wells in the area. Yet, this method remains traditional and often fails to effectively replicate past experiences and data. Additionally, the planned settings are frequently applied throughout the bit run without considering the actual down-hole conditions, which complicates the acquisition of comprehensive and high-quality data [9].

It has recently been demonstrated in the petroleum engineering sector that Artificial Neural Networks (ANNs) and simulation are both very good tools for forecasting the behavior of various aspects of petroleum design in the future [13],[14],[15],[16],[17],[18],[19]. For instance, Ozbayoglu et al. [20] completed the first artificial intelligence (AI) study on hole cleaning in both horizontal and deviated wells. They used feed-forward neural networks with a back-propagation learning algorithm (BPNN) to examine the cutting bed height. Rooki et al. [21] and Rooki and Rakhsh Khorshid [22] employed radial basis neural networks (RBFN) and BPNN for hole-cleaning prediction in foam drilling operations. They used experimental data involving pressure and temperature conditions, foam performance, foam velocity, eccentricity, and pipe rotational speed (RPM) as input parameters, while the output parameter was cutting concentration. Al-Azani et al. [23] concluded that the cutting concentration in the wellbore can be accurately predicted using a Supervised Vector Machine (SVM). However, to date, no experimental examinations of hole cleaning during drilling operations using AI approaches have been conducted. By measuring cutting concentration in the wellbore, this work attempts to create an ANN model that can be used to indirectly predict the hole cleaning efficiency. Transport efficiency (TE) is defined as the output parameter and five input parameters were used as model input parameters during neural network training. Ultimately, drilling engineers can utilize this prediction range to detect issues and guide decision-making. The validated neural network model can be used to accurately estimate hole cleaning efficiency in real-time.

## 2. Methodology: Data Description and Building ANN Model

In this work, a transport efficiency prediction model is developed using Artificial Intelligence (AI) tools. It is proposed that an Artificial Neural Network (ANN) provides a nonlinear function between inputs and output data for data processing and complex system modeling. These technologies use artificial neurons interconnected in a manner similar to biological neural networks and are based on several processing methodologies [24]. Typically, a multilayer neural network consists of input, hidden, and output layers. Typically, one hidden layer is tried for neural network model size optimization, as illustrated in Fig. 1. An artificial neural network with two feed-forward backpropagation network (BPNN) layers was used in this study. Additionally, two transfer functions with varying quantities of concealed neurons were used: the Log sigmoid and the Hyperbolic Tanh. The architecture, training network, and data preprocessing all have a significant impact on the network's efficacy and dependability [15],[25]. As a result, three subsets of the available data are optimally separated: training, validation, and testing. The total data are subsets into 70, 15, and 15 percent, respectively.

The information utilized to construct the AI models is mentioned in Table 1. Over 1620 data points from experimental activities were gathered and utilized as input data. These data sets include inclination angle, particle density, flow rate, drill-string rotational speed, and particle diameter. Additionally, data were carefully filtered to eliminate redundant and noisy information, which ensured the network was not affected by anomalous hole-cleaning data. Choosing the right network size is essential for maximizing simulation time [10],[25]. To determine the optimal model design, a sensitivity analysis was performed on the different parameters. Numerous attributes, including the number of neurons, training and transfer functions, and the number of hidden layers, were assessed to ascertain their impact on the ANN model's accuracy. Sensitivity analyses were implemented and evaluated using the correlation coefficient (R). Additionally, the neural network that performs the best is the one that most effectively fits the dataset.

**Table 1.** Transport efficiency vs. selected parameters input parameters for the ANN model.

| Input | Output |
|---|---|
| Degree of inclination (°) | |
| Particle density (ppg) | |
| Flow rate (gpm) | Transport efficiency (TE) |
| Rotational per minute (RPM) | |
| Particle diameter (in) | |

## 3. Results and Discussion

This section examines the results obtained from the ANN models developed to estimate transport efficiency using the experimental values. Four distinct training functions were used to construct a feed-forward backpropagation network. To optimize the proposed ANN code, twelve primary scenarios were created. The outcomes were evaluated to determine the optimal model, using the parameters indicated in Table 2. For this investigation, four distinct learning functions-LM, RP, SCG, and BR-were modified. There are two adaptation learning functions used: LEARNGD and LEARNGDM. In addition, to determine which ANN model was more effective in predicting TE, the TANSIG and LOGSIG transfer functions were implemented. We have checked the code running for every chosen parameter, and the outcomes were compared by means of the correlation coefficient ($R$) with the actual data. Consequently, the optimal model parameter combination for process optimization was identified and put into practice. The data sets' training-to-testing and validation ratios were chosen to be 70% and 30%, respectively. This indicates that 243 data points were selected for each testing and validation procedure, while 1134 data points were chosen for training.

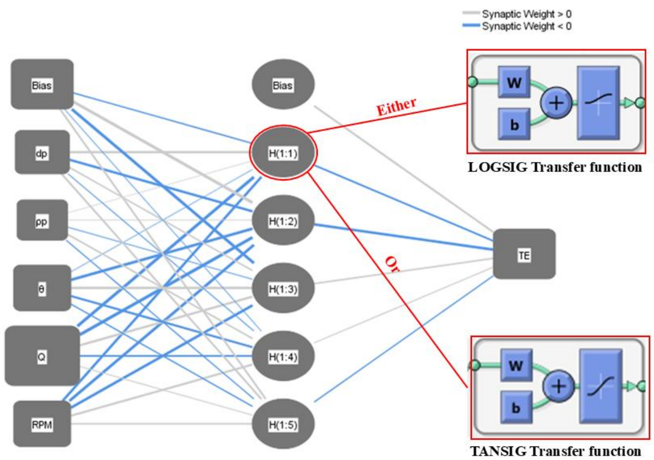



**Fig. 1.** The architecture of the ANN model that was constructed.

Figures 2-5 display the cross-plots for the ANN results for the model training, testing, and validation procedures. In general, the GDM adaptation learning function works better than the GD function when comparing the outcomes of anticipated and real TE utilizing the TANSIG transfer function, GDM versus GD learning function, and LM training function (Fig. 2 and Fig. 3). For example, the GDM function yields a correlation coefficient ($R$) of 97.45 for 10 neurons, whereas the GD function yields a correlation coefficient of 97.08. These results overperform the results obtained by Azani et al. [23], in which the SVM model yielded correlation coefficients between the measured and the predicted values in the training and testing stages of 94% and 93%, respectively.

The results show that as the number of neurons increases, the model's accuracy in terms of $R$ for preparation and analysis improves. For instance, when the number of neurons increased from two to ten, the $R$ values of actual and anticipated TE rose from 94.50% to 97.45%. Conversely, Figs. 4 and 5 display the various $R$ values of the LOGSIG purpose for testing, training, and validation; the optimal outcomes are achieved with ten neurons. The GDM works better with a limited number of neurons for the LOGSIG transfer function. This indicates that, compared to the GD model, the tested ANN model with two and four neurons had a greater value of $R$ for the GDM. Using the GD function, however, yields greater $R$ values when the number of neurons is increased to 6, 8, and 10 (see Table 3). For example, using two neurons with GDM function yielded $R$ values of 95.9%, 95.12%, and 93.42% for testing, training, and validation, respectively. Using two neurons and the GD function, the corresponding $R$ values of actual and projected TE are 94.62%, 94.27%, and 95.54%. Therefore, we might suggest combining the GD adaptation learning function with the LOGSIG transfer function for improved prediction accuracy under certain configurations.

Moreover, the results show that the LOGSIG transfer function has somewhat outperformed the TANSIG function's estimates of the outcomes at two and four neurons. However, the TANSIG function works better when there are more neurons. The correlation factor between several ANN models using TANSIG and LOGSIG transfer functions, as well as the GD and GDM adaptation learning functions, is illustrated in Fig. 6. In conclusion, we might propose that the TANSIG transfer function typically outperforms the LOGSIG transfer function with more neurons when combined with the GDM adaptation function. Table 3 provides a summary of the sensitivity analysis of every parameter used with the ANN model. Sensitivity study demonstrates that the training functions have little effect on the constructed ANN model and, thus, on the TE prediction performance in general. Thus, utilizing the TANSIG transfer on in conjunction with the GDM adaptation function, we might propose the following model for TE prediction:

$$TE_n = \left[\sum_{i=1}^{N} w_{2_i}\left(\frac{2}{1+e^{-2(w1_{i,1}dc+w1_{i,2}\rho_c+w1_{i,3}\theta+w1_{i,4}Q+w1_{i,5}RP+b1_i)}}\right) - 1\right] + b2 \tag{1}$$

$$\mathrm{TE_{de-n}} = \frac{(\mathrm{TE_n}+1)(\mathrm{TE_{max}}-\mathrm{TE_{min}})}{2} + \mathrm{TE_{min}} \tag{2}$$

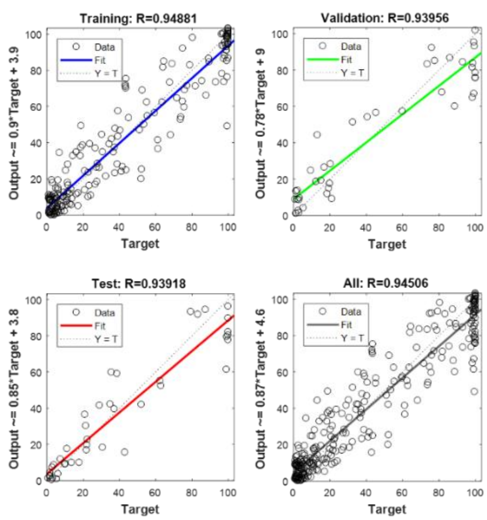
The weights of the hidden and output layers are W1 and W2, respectively; the number of neurons is N; the bias of the layer is indicated by b; and the bias of the output layer is denoted as b2. **Error! Reference source not found.** below shows the values of the different parameters used in the above equations.

**Table 1.** Parameters of the suggested model equations.

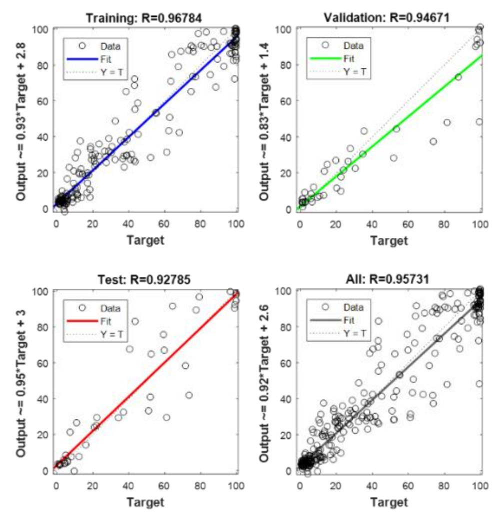
| | | w1 | | | W2 | b1 | b2 |
|---|---|---|---|---|---|---|---|
| -0.161 | 0.2185 | -0.5057 | -1.238 | -0.4264 | -1.078 | 0.61619 | 0.1419 |
| -20.198 | 0.12504 | 75.3855 | 15.0679 | 3.7924 | -0.0892 | 41.3223 | |

**Table 3.** Implemented ANN model parameters

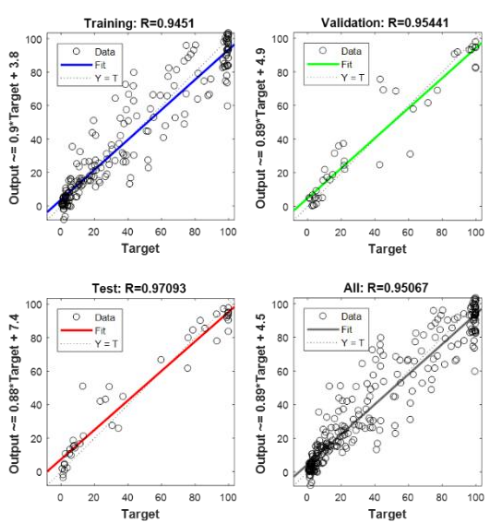
| Training Function | Learning Function | Transfer Function | Number of Neurons in Hidden Layer | Number of Hidden Layer | Training, Testing, and Validation Ratio |
|---|---|---|---|---|---|
| Lm | GDM / GD | Hyperbolic tangent | 2–10 | 1 | 70, 15, 15 |
| | GDM / GD | Logistic sigmoid | 2–10 | 1 | 70, 15, 15 |
| RP | GDM / GD | Hyperbolic tangent | 2–10 | 1 | 70, 15, 15 |
| | GDM / GD | Logistic sigmoid | 2–10 | 1 | 70, 15, 15 |
| SCG | GDM / GD | Hyperbolic tangent | 2–10 | 1 | 70, 15, 15 |
| | GDM / GD | Logistic sigmoid | 2–10 | 1 | 70, 15, 15 |
| BR | GDM / GD | Hyperbolic tangent | 2–10 | 1 | 70, 15, 15 |
| | GDM / GD | Logistic sigmoid | 2–10 | 1 | 70, 15, 15 |



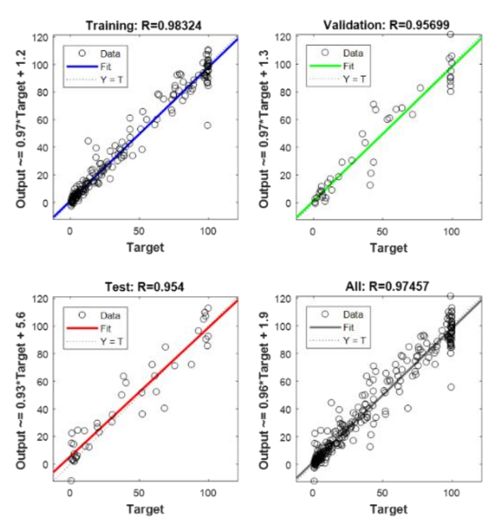

Tanh-2N-GDM




Tanh-6N-GDM

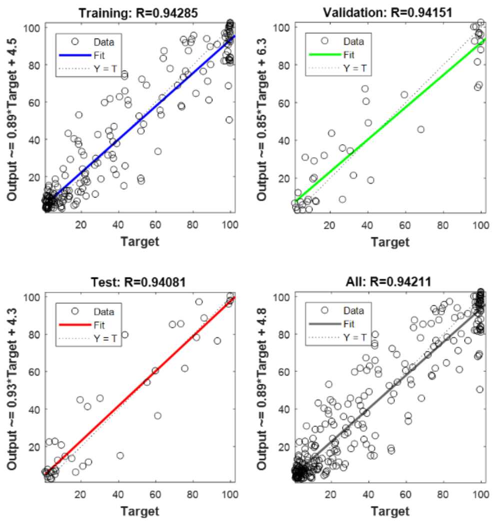



Tanh-4N-GDM

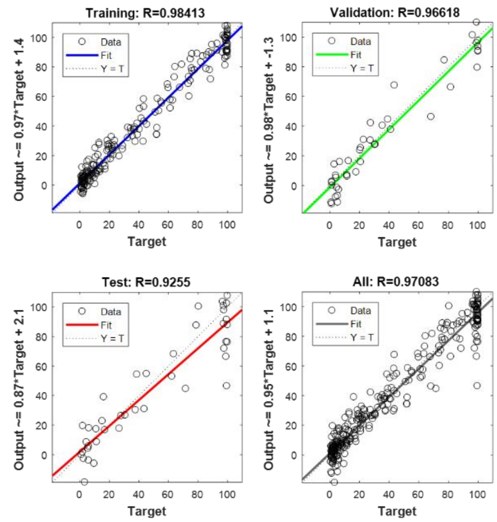



Tanh-10N-GDM

**Fig. 2.** Actual and anticipated TE utilizing the Tanh transfer function, GDM learning function, and LM training function

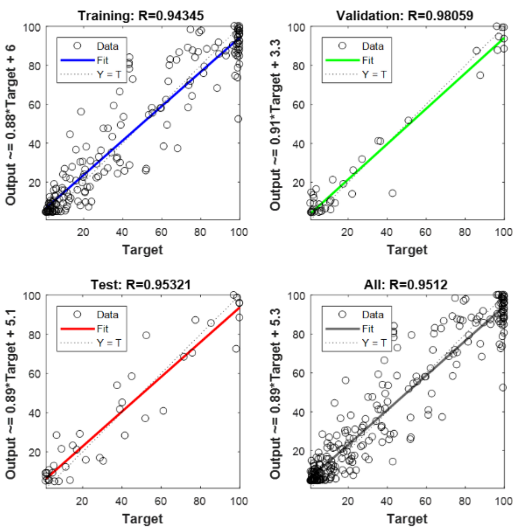



Tanh-2N - GD

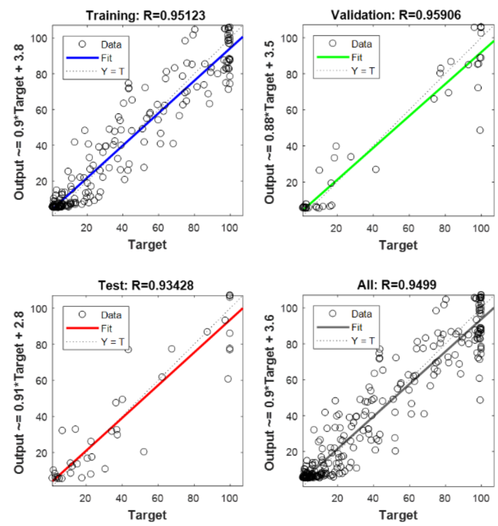



Tanh-10N-GD

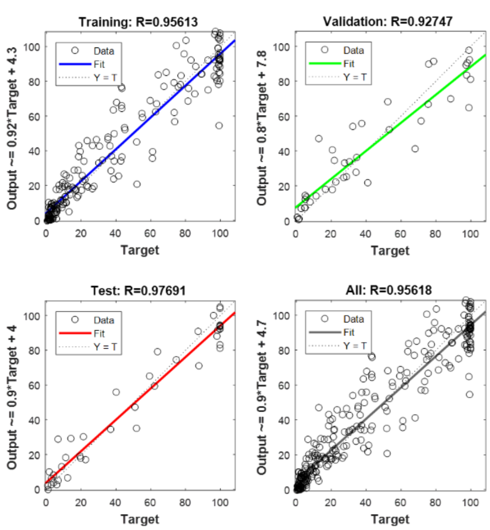
**Fig. 3.** Predicted and actual TE using the Tanh transfer function, GD learning function, and LM training function.



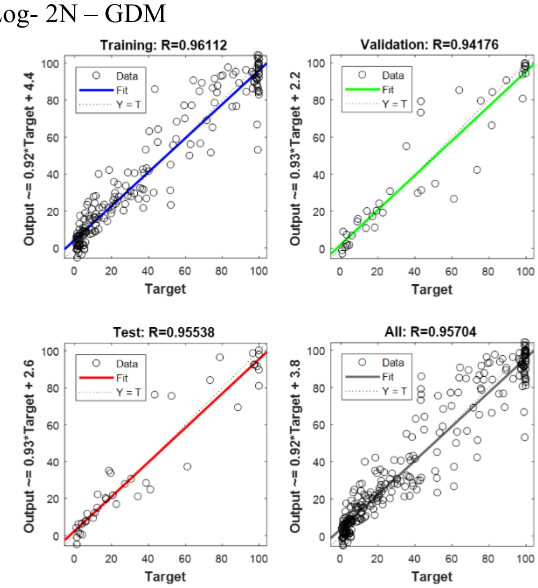

Tanh-4N – GD



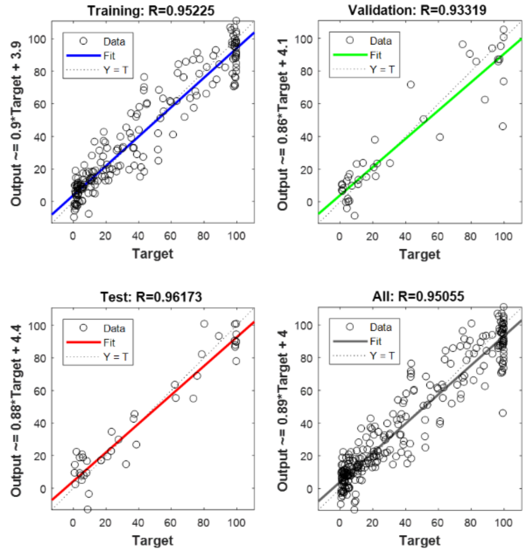

Log- 2N – GDM



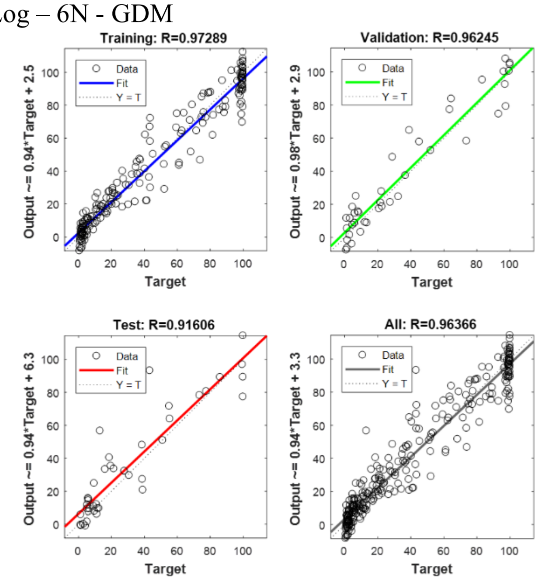

Tanh- 6N-GD




Log – 4N – GDM

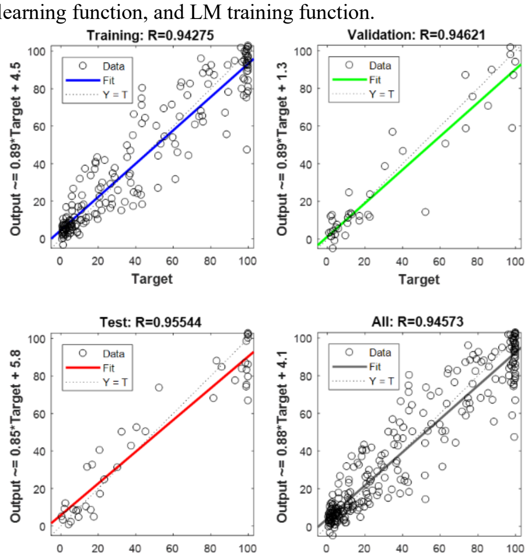



Log – 6N - GDM

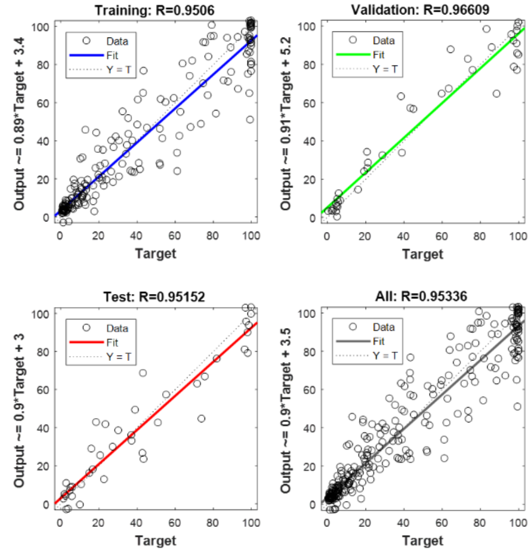



Log – 10N – GDM

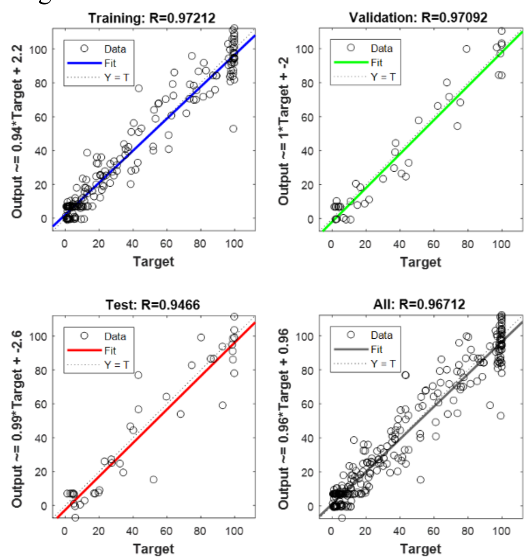
**Fig. 4.** Actual and anticipated TE utilizing the Sigmoid transfer function, GDM learning function, and LM training function.



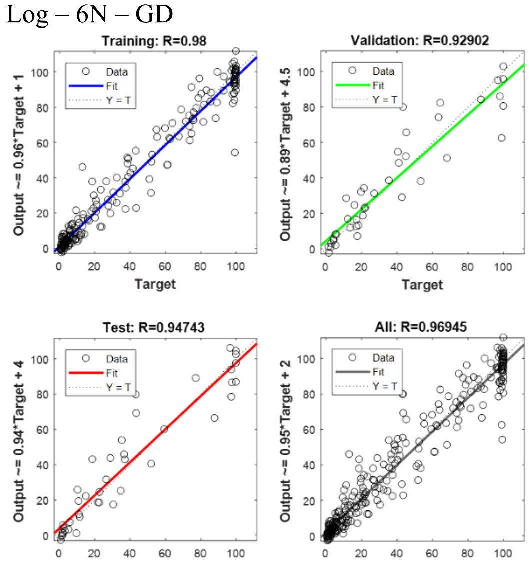

Log – 2N – GD




Log – 4N - GD




Log – 6N – GD




Log – 10N – GD

**Fig. 5.** Actual and anticipated TE utilizing the Sigmoid transfer function, GD learning function, and LM training function.

**Table 4.** Sensitivity analysis of all parameters applied for ANN model.

| Transfer Function | Learning Function | Training Function | Number of Neurons in Hidden Layer | | | | |
|---|---|---|---|---|---|---|---|
| | | | 2 | 4 | 6 | 8 | 10 |
| TANSIG | GDM | LM | 94.5 | 95.06 | 95.73 | 95.45 | 97.45 |
| LOGSIG | GDM | | 94.99 | 95.7 | 95.05 | 96.62 | 96.36 |
| TANSIG | GD | | 94.21 | 95.12 | 95.61 | 97.01 | 97.08 |
| LOGSIG | GD | | 94.57 | 95.33 | 95.71 | 97.08 | 96.94 |
| TANSIG | GDM | RP | 94.74 | 96.19 | 96.65 | 97.79 | 97.15 |
| LOGSIG | GDM | | 94.56 | 95.81 | 95.49 | 97.27 | 97.01 |
| TANSIG | GD | | 95.24 | 95.53 | 95.67 | 97.1 | 96.83 |
| LOGSIG | GD | | 95.39 | 96.1 | 95.95 | 96.65 | 97.2 |
| TANSIG | GDM | SCG | 94.93 | 95.98 | 97.04 | 96.01 | 97.36 |
| LOGSIG | GDM | | 95.17 | 95.61 | 96.8 | 95.46 | 97.39 |
| TANSIG | GD | | 95.34 | 95.5 | 95.04 | 96.77 | 96.88 |
| LOGSIG | GD | | 95.39 | 95.92 | 96.59 | 96.89 | 97.55 |
| TANSIG | GDM | BR | 95.41 | 96.55 | 94.65 | 97.07 | 97.29 |
| LOGSIG | GDM | | 95.3 | 96.48 | 95.31 | 96.8 | 97.23 |
| TANSIG | GD | | 95.26 | 96.48 | 96.68 | 94.92 | 97.25 |
| LOGSIG | GD | | 95.39 | 96.02 | 96.65 | 96.59 | 97.19 |

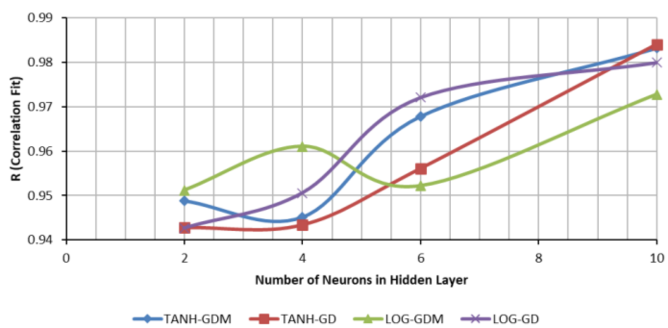



**Fig. 6.** *R* correlation vs. number of neurons using different ANN training functions.

## 4. Conclusions

This article predicts nonlinear cutting transport efficiency using a neural network with multiple layers modelling. One hidden layer, two transfer functions (TANSIG and LOGSIG), four distinct training functions, and two to ten neurons for the hidden layer were all used in the analysis of the constructed ANN model. The model's accuracy increased as the number of neurons increased, according to the results. The GDM adaption learning function for the TANSIG transmission purpose generally outperforms the GD purpose. Results also indicate that the LOGSIG transfer function has subtly overperformed the results estimated by the TANSIG function at two and four neurons. Finally, we could conclude that using the TANSIG transfer function with the GDM adaption learning function generally performs better than the LOGSIG transfer function with higher numbers of neurons. Therefore, we suggested a novel predictive model the transport efficiency in wells.

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