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Original Article

Prediction and Optimization of Gas Lift Performance Using Artificial Neural Network Analysis

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Abstract

Gas lift is one of the most widespread methods of artificial lift technologies used when wells' production rate drops below the economic limit. Gas Lift is employed to maintain the production above the available limit by means of injecting gas into the tubing through the casing–tubing annulus and a gas lift orifice installed in the tubing. Gas lift has been widely used in the oil fields that suffer from sand production. It is also used in deep and deviated wells and on offshore platforms. Lifting costs for a large number of wells are generally low. However, capital costs of compression stations are very high, so it is necessary to optimize gas lift wells by determining the optimum gas lift injection rate and optimum oil rate for each well. In this paper, conventional nodal analysis models using Pipesim software were used to predict the optimization parameters based on wells flowing survey, reservoir and well parameters and calculations of multiphase flow behavior. Artificial neural network (ANN) models were also used based on gas lift databases and gas lift monitoring systems. ANN models were trained to obtain the optimum structure and then tested against pipesim models. Also, this paper presents a new theory about the relative importance of gas lift system input data in predicting optimum parameters of gas lift system. It has been concluded that ANN has an excellent competing ability for gas lift optimization prediction compared to conventional methods and can be used interchangeably. This technique can considerably help in the immediate optimal design of gas lift wells.

Keywords: Gas Lift Performance and Optimization, Prediction, Artificial Neural Network, Optimum Oil Rate, Optimum Gas Lift Rate, Pipesim, Matlab.

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Nomenclature

AAPRE	Average Absolute Percent Relative Error
ANN	Artificial Neural Network
APRE	Average Percent Relative Error
G/L	Gas Lift
GLR	Gas-Liquid Ratio (SCF/STB)
$IM(X_p)$	Importance of input variable (X_p)
I_{pj}	P^{th} Input weight in j^{th} hidden layer
Max. PRE	Maximum Percent Relative Error
Min. PRE	Minimum Percent Relative Error
MSE	Mean Squared Error
n_h	Number of neurons in the hidden layer
n_p	Number of input variables
O_j	Output layer weight for j^{th} hidden layer
P_{inlet}	Inlet Pressure (Psi)
PLT	Production Logging Tool
P_{node}	Node Pressure (Psi)
P_{outlet}	Outlet Pressure (Psi)
P_{sep}	Separator Pressure (Psi)
PVT	Pressure, Volume, Temperature
P_{wh}	Wellhead Pressure (Psi)
q_g	Gas Lift Injection Rate (MMSCFD)
R	Correlation Coefficient
R^2	Correlation Coefficient Squared
RMSE	Root Mean Squared Error
R_P	Average Reservoir Pressure (Psi)
SD	Standard Deviation
SSD	Slide Sleeve Door
ΔP	Pressure Drop (Psi)

Introduction

The operation of gas lift well resembles that of a naturally flowing well. Gas is injected into the tubing through a gas lift valve at certain depth and the increased gas/liquid ratio from the valve to the surface causes a decrease in the hydrostatic pressure gradient in the tubing, hence, decreases the bottom hole pressure. The only difference between this type of operation and a flowing well is that the gas-liquid ratio changes at injection point in the tubing for the gas lift well. A gas lift well schematic and pressure traverse is shown in Figure 1.

There is an optimum GLR that will minimize the pressure drop over the tubing at a given liquid flow rate. Too much gas increases the pressure drop because friction effects increase. One, therefore, expects that for a producing well there will be an optimum GLR at which gas can be injected to maximize the oil production rate.

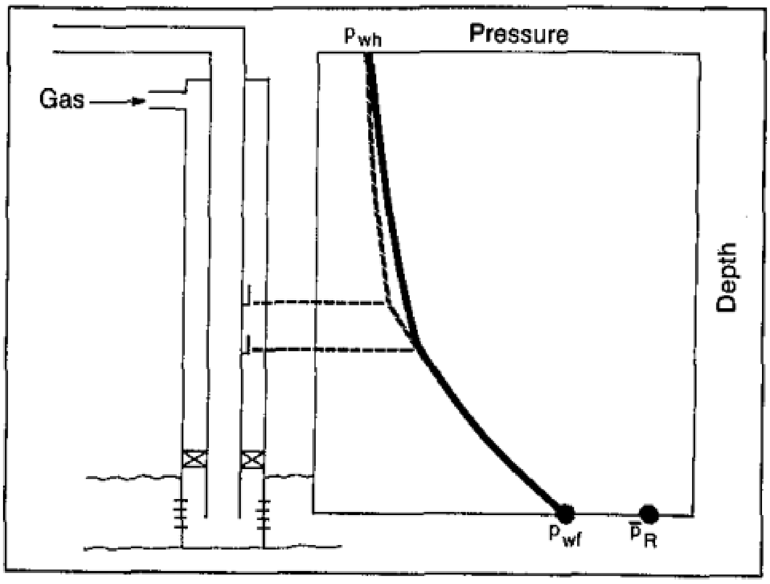

Figure 1: Gas Lift Well Schematic

If gas lift rate is gradually increased, the production rate initially increases because the fluid density is reduced. However, as the gas injection rate is increased further, pressure losses due to friction become more crucial, and the production rate starts to decline as shown in Figures

2 & 3. Figure 4 represents another method to determine the optimum gas lift rate (or optimum GLR) which is to draw outflow curve with different G/L rate (or GLR) and determine the rate at which the outflow curve intersects the inflow curve at maximum oil production rare, this is the optimum G/L rate (or optimum GLR). According to the lift gas availability, the compression cost of the gas, and the income of the oil sale, the economic optimum injection rate may be less than that required to obtain the maximum oil rate.

In this paper, the gas lift optimization is done using conventional nodal analysis using Pipesim software and new artificial neural network models to compute the optimal values of gas injection rate and oil rate of a gas lift production system. This work utilizes test data of Egyptian gas lift fields for both Pipesim and ANN models then compares the results of the two methods.

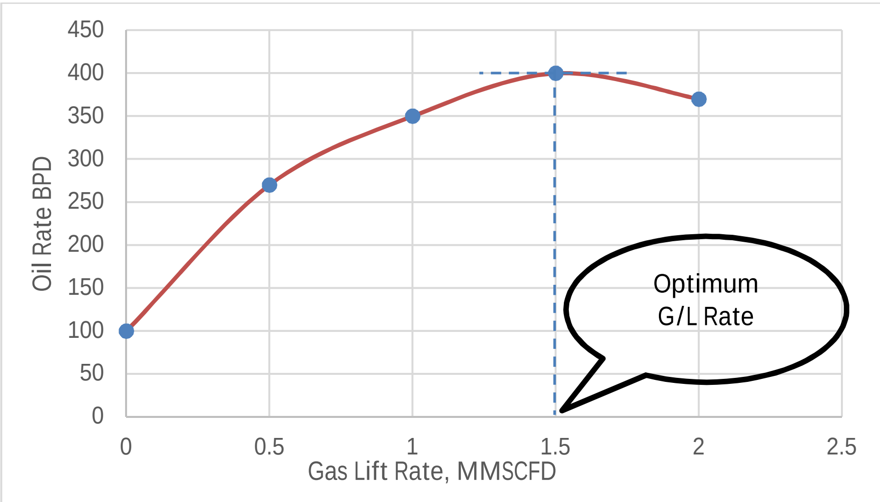

Figure 2: The Optimal Gas Lift Rate

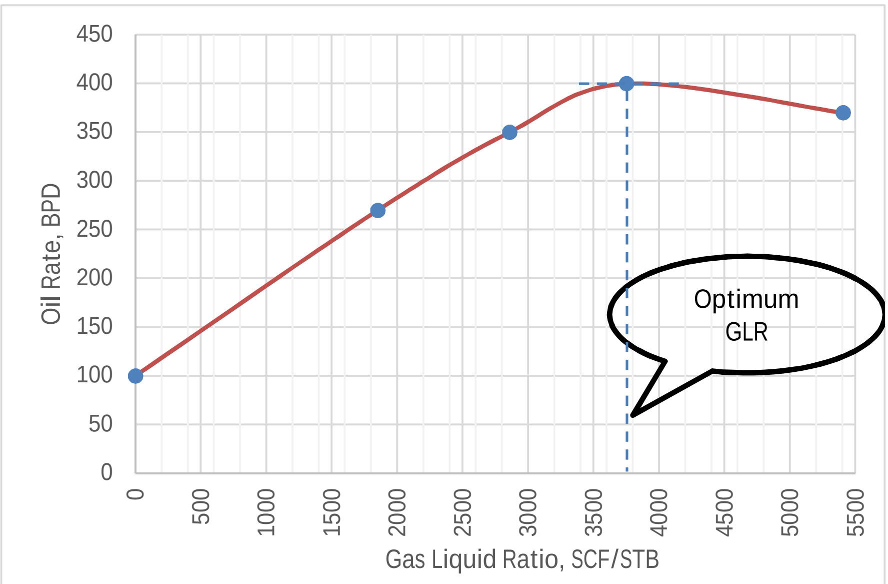

Figure 3: The Optimal GLR Point

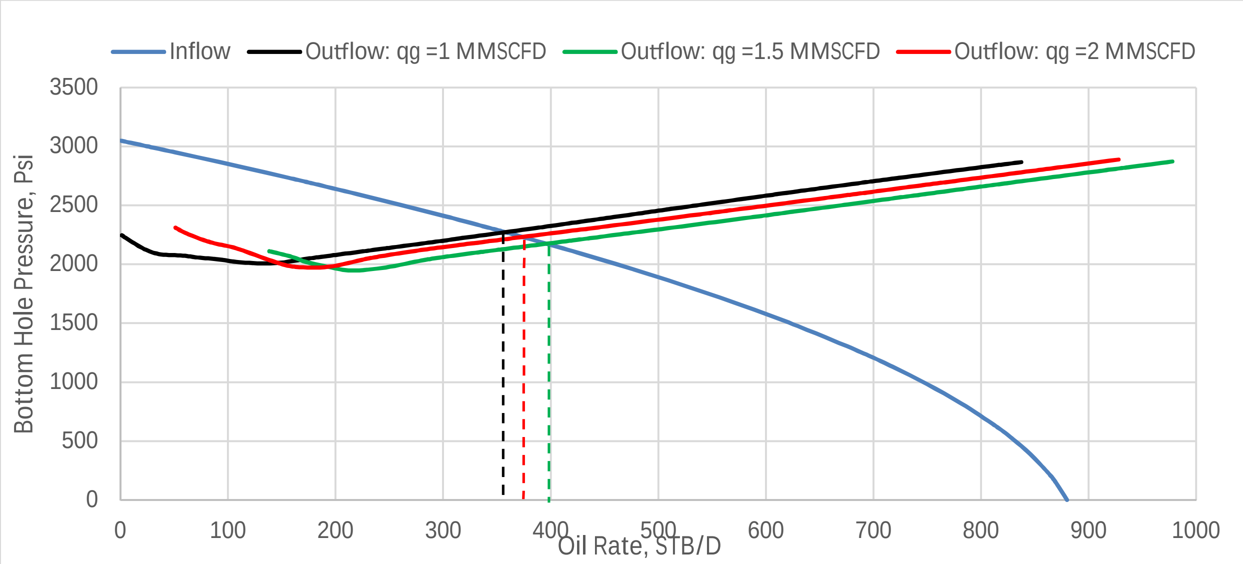

Figure 4: Gas Lift Well Nodal Analysis.

Literature Review

Neural network research can be followed back to 1943 once the first artificial neuron was proposed by Warren McCulloch and the Walter Pits. But the technology existed at that time was an obstacle against achieving more progress. Rosenblatt (1957) designed the perceptron (neuron with weighted inputs). Widrow (1962) designed a network called Adeline. After that, the neural network's research stopped for twenty years (Hertz *et al.*, 1991). Then, Hopfield (1982) introduced new algorithms, like backpropagation. Since then, neural network applications have been widely expanded (Mohaghegh, 2000).

ANNs have been used to solve complex problems in the petroleum industry, especially the problems that cannot be solved using conventional modeling tools. The applications of ANN in the petroleum industry can be found in its four branches: Exploration, Drilling, Reservoir and Production. Here are some examples from literature of ANN applications in Production branch: Thomas & Pointe (1995) used ANNs to identify conductive fractures. A. Elgibaly *et al.*, (1998) used Neural Networks in determination of Optimal Hydrate Inhibition Policies. Faga, & Oyeneyin (2000) used ANNs to get grain size distribution for gravel-pack completion. Salehi *et al.*, (2009) used ANNs to predict casing collapse issues. Khan *et al.*, (2018) utilized ANNs to forecast water saturation in complex lithologies. Tariq (2018) employed ANNs in bottom hole flowing pressure prediction. Olabisi *et al.*, (2019) used ANN for Prediction of Hydrate Formation Temperature.

Also, ANN has many applications concerning gas lift fields. Khamehchi *et al.*, (2009) used ANN to predict gas lift parameters (gas injection rate and depth of injection). Ranjan *et al* (2015) used ANN for Gas Lift Optimization. Shokir *et al.*, (2017) used ANN and integrated production modeling in optimizing of Ras Shokir gas lift field in the Gulf of Suez in Egypt. Khan *et al.,* (2020) used ANN for Oil Rate Prediction in Artificial Gas Lift Wells.

Conventional Methodology: Nodal Analysis

Nodal analysis was first introduced by Gilbert in 1954 and was discussed by Nind in (1964) and Brown in 1978. Nodal analysis requires selecting a node and calculating its pressure, starting at the constant pressure in the system such as Average reservoir pressure (R_P) as the inlet pressure and either wellhead pressure (P_{wh}) or separator pressure (P_{sep}) as the outlet pressure. Any point in the system may be selected to be the required node. The expressions for the inflow and the outflow of the node can be expressed as:

$$P_{node} = P_{inlet} - \Delta P(upstream\ components) = P_{outlet} + \Delta P(downstream\ components) \quad (1)$$

The Pipesim software is a useful tool for simulating actual production systems and evaluating their responses to different production cases, challenges, and the impact of various solutions on production systems before field implementation.

To perform nodal analysis via Pipesim software, some data first were gathered to build well models. These data are: the wellbore diagram including (tubing size, well depth, end of tubing depth, downhole equipment such as packers and SSDs), well deviation survey indicating measured depths and true vertical depths, artificial lift system used in the well which in our case is gas lift system and its parameters (valve type, injection depth and surface gas injection pressure). Also, one important data set is the reservoir producing zone including (perforation depth, productivity index, reservoir pressure and temperature, and PVT properties of the produced fluids). The multiphase flow correlations were selected based on well-flowing surveys or PLT data, in these models, Hagedorn and Brown correlations were used for vertical flow, and Beggs and Brill correlations were used for horizontal flow as they were found to be the most convenient correlations for gas lift wells, then nodal analysis tool was used to give the optimum oil rate as in Figure 5. Also, the system analysis tool in Pipesim was used to determine the optimum gas lift injection rate.

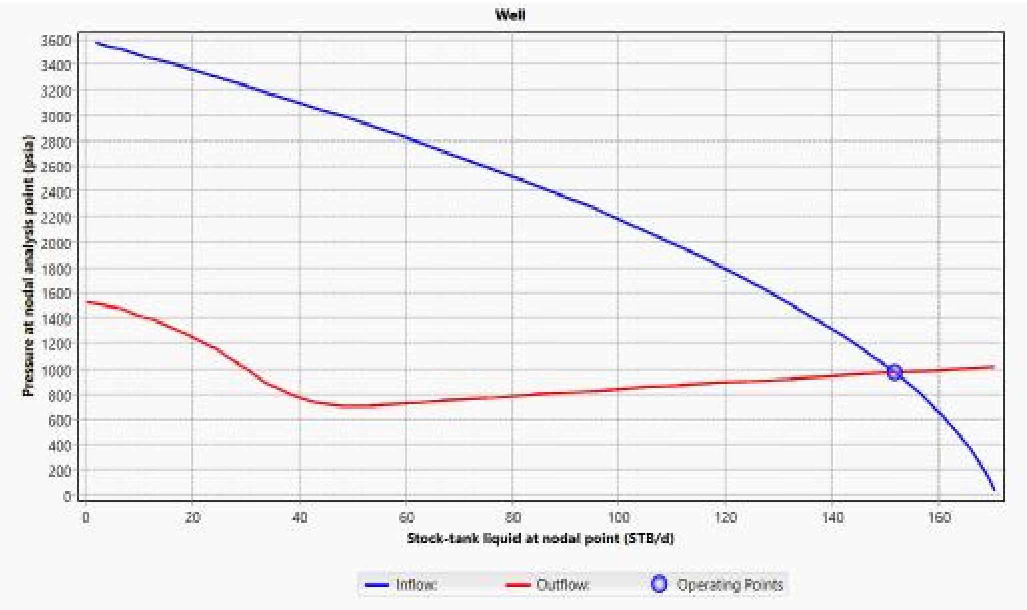

Figure 5: Example of Nodal Analysis Using Pipesim Software

Artificial Neural Network

ANN is a model that processes information imitating the mechanism by which biological nervous systems process information. It consists of a number of connected processing elements (neurons) that work together to solve specific problems. Neural networks can be used to understand patterns and discover trends that are too complex to be noticed by either humans or other computer techniques.

Biological Basis

ANNs are generally presented as systems of neurons organized in different layers and neurons of each layer are connected through weights. These “neurons” can be trained and used to work out values from inputs, and are capable of machine learning and pattern identification (Kumar, 2012). The understanding of ANN can be made easier by understanding the mechanism of biological neuron networks.

The basic component of the biological neural network is a neuron. A neuron mainly consists of three parts: dendrites, body (soma), and axon (Figure 6). Dendrites are the tree-like structure that receives the signal from neighboring neurons. Axon is a thin cylinder that passes the signal from one neuron to another. At the end of the axon, the contact to the dendrites is made through a synapse (synaptic connections). The signal is received by the dendrites, transported to the neuron cell body where they are processed and, converted to output, and transmitted through the Axon to the next neuron.

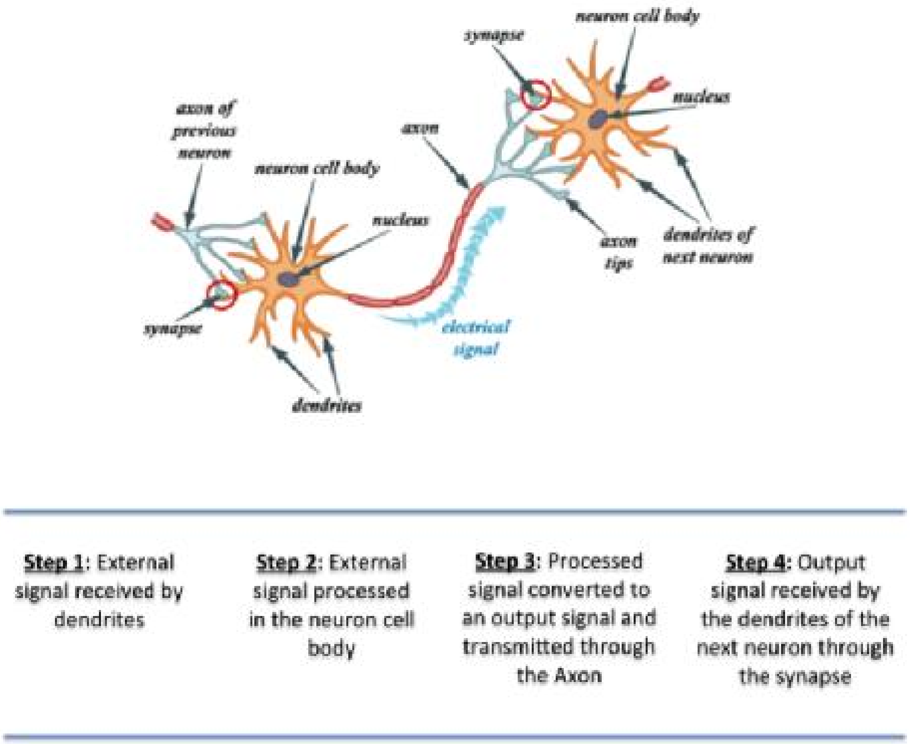

Figure 6: Two Bipolar Neurons (After Mohaghegh, 2000**).**

ANN Structure

ANNs are developed based on mathematical models with the following assumptions (Mohaghegh, 2000):

1. The information is processed through nodes (neurons).
2. There are connecting links between the neurons that allow the information to pass through.
3. Each connection link has its weights.
4. Once the inputs received by the neurons, the neurons will apply an activation function to calculate the outputs.

Figure 7 shows an artificial neuron, the outputs from other neurons are multiplied by their weights and enter the neuron as inputs. These inputs are then summed and the activation function of the neuron is applied which leads to an output. An artificial neural network consists of one input layer, one or more hidden layers that extract features from the data, and one output layer.

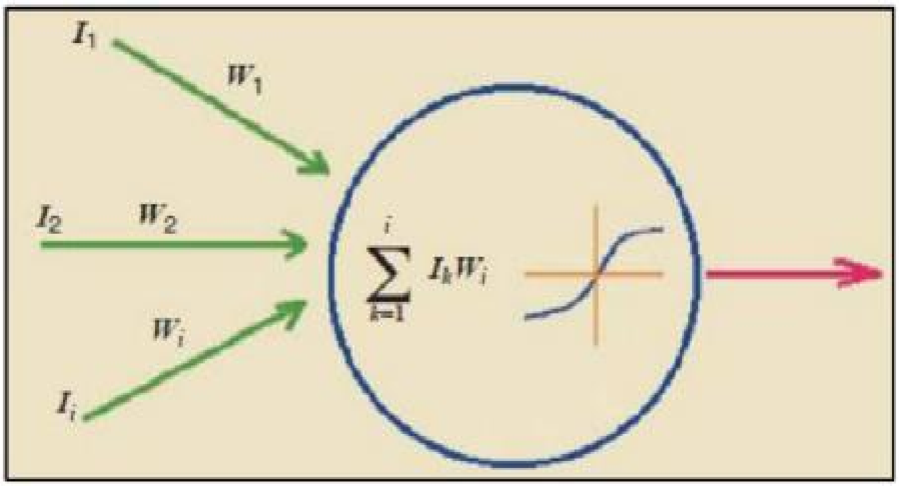

Figure 7: Schematic of Artificial Neuron (After Mohaghegh, 2000**)**

ANN Strategy

Neural networks receive data, train themselves via learning rule to recognize the patterns in this data, and then predict the outputs for a new set of similar data (Figure 8).

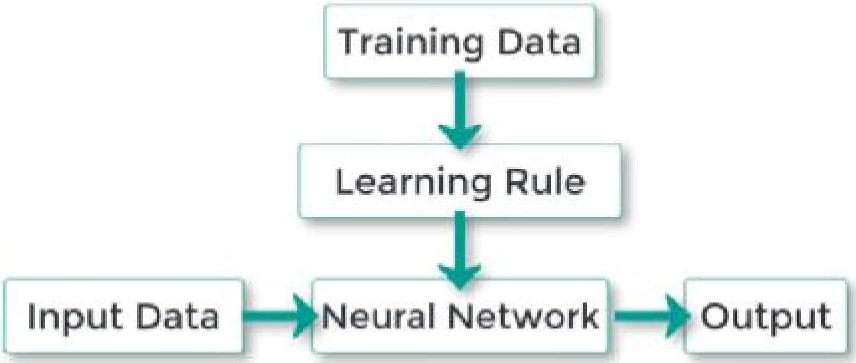

Figure 8: The Strategy of Neural Network.

The most widely used network is known as the Feed Forward Back Propagation Neural Network (which is in use in this paper). This type of neural network is excellent at prediction and classification tasks. Neural networks require the use of training patterns and involve a forward propagation step followed by a backward propagation step. The forward step sends an input signal through the neurons at each layer computing of an output value. This output is then compared with the desired output and the error is calculated and back-propagated through the system to modify the weights which control the network.

Adopted Methodology

Data Acquisition

Adopted ANN in this work, depends primarily on wells' actual test data obtained from test separator and measuring devices installed on both flowlines and gas lift lines. Also, because ANN can work with incomplete information and has fault tolerance when dealing with data with great uncertainty which is considered a great advantage of ANN over analytical conventional methods, downhole data obtained from static and flowing surveys, production logging tools (PLT) and reservoir rock and fluid properties obtained from PVT lab analysis and core lab analysis were used in this work nevertheless the deficiency of regular bottom hole flowing surveys and uncertainty of downhole data.

In this paper, 11144 data points of 30 elements were gathered, investigated for inconvenience and checked, 28 elements were selected as inputs and 2 elements were selected as outputs representing: oil flow rate (BPD), Gas lift rate (MMSCFD). The minimum and maximum values of the input parameters used in the developed ANN are listed in Table 1.

This data set was randomly divided into 70% for training, 15% for validation, and 15% for the primary test. Training data are used to improve the network according to their error. Validation data are used to evaluate network generalization, and to stop training when generalization stops improving. Test data do not affect training, so they provide an independent measure of network performance during and after training.

Table 1: Minimum and Maximum Values of the Input and Output Variables of the Developed ANN

Parameter	Min.	Max.	Parameter	Min.	Max.
Well Head Pressure (Psi)	50	650	Reservoir Temperature (°f)	130	280
Flow Line Pressure (Psi)	40	440	Bottom Hole Flowing Pressure (Psi)	125	4349
Flow Line Temperature (°c)	8	95	Productivity Index (STB/Psi)	0.0502	42.98
Separator Pressure (Psi)	36	420	Reservoir Porosity (percent)	8	27
Annulus Pressure (Psi)	0	1350	Reservoir Permeability (md)	1.4	700
Flow Line Length (m)	654	11161	Oil Gravity (API)	24	45
Choke Size, (1/64 in)	24	128	Formation Gas-Liquid Ratio (SCF/STB)	240	10000
Water Cut (Percent)	0	98.3	Gas Gravity	0.712	0.814
Kick-off Point (m)	350	3616	Oil Formation Volume Factor (RB/STB)	1.012	5
Inclination (°)	0	65	Oil Viscosity (cp)	0.1	0.453
Gas Injection Depth (m)	320	3406	Bubble Point Pressure (Psi)	1032	5511
Orifice Port Size (in)	0.125	0.5	Gas Formation Volume Factor (RB/MSCF)	0.852	3.18
Reservoir Depth (m)	350	3616	Gas Viscosity (cp)	0.0146	0.0285
Net Pay Thickness (m)	1.5	46	Gas Lift Rate (MMSCFD)	0	3.8
Reservoir Pressure (Psi)	491	4900	Oil Flow Rate (BPD)	2	1947

ANN Design and Training

The optimum architecture of the developed ANN was determined by trial and error. The parameters varied were: training function, transfer function, number of hidden layers, and number of neurons in each layer. The optimum number of neurons in each layer depends on the complexity of the problem. If the number of neurons is too few, the algorithm does not converge to a minimum during the training. At the opposite, too many neurons result in over-fitting of the data causing poor performance.

The developed neural network contained 28 input variables, one hidden layer with 10 neurons and 2 output variables. Log-Sigmoid function (logsig) was used as a transfer function in the hidden layer. The linear function (purelin) was used in the output layer of the network. The training algorithm used is Levenberg-Marquardt (trainlm), this algorithm typically requires more memory but less time. Training automatically stops when generalization stops improving, as indicated by an increase in the mean square error of the validation samples.

The architecture was retrained many times (at least 3 times) till obtaining the best results which were saved for further testing. Figure 9 shows the optimum architecture for gas lift optimization.

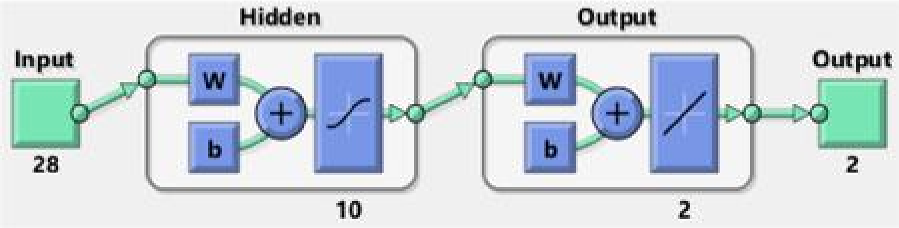

Figure 9: The Neural Network Architecture

There are many parameters used to evaluate the trained neural network. Mean squared error (MSE) is used to measure network performance as in Figure 10. Figures 11 & 12 show the error histogram of oil rate and G/L rate outputs respectively, it is shown that 41% of oil rate output data error lies between -10 and 10 BPD and 78 % lies between -30 and 30 BPD. Also, 26% of G/L rate output data error lies between -0.1 and 0.1 MMSCFD and 61.4 % of G/L rate output data error lies between -0.3 and 0.3 MMSCFD. Regression (R) values measure the correlation between outputs and targets, a close relationship has R value close to 1, and a random relationship has R value close to zero. R values of training, validation and testing data are 0.99687, 0.99675 and 0.99677 respectively, also, all input data have regression value of 0.99683 as in Figure 13. These parameters indicate efficient trained neural network which enables proceeding to the next step.

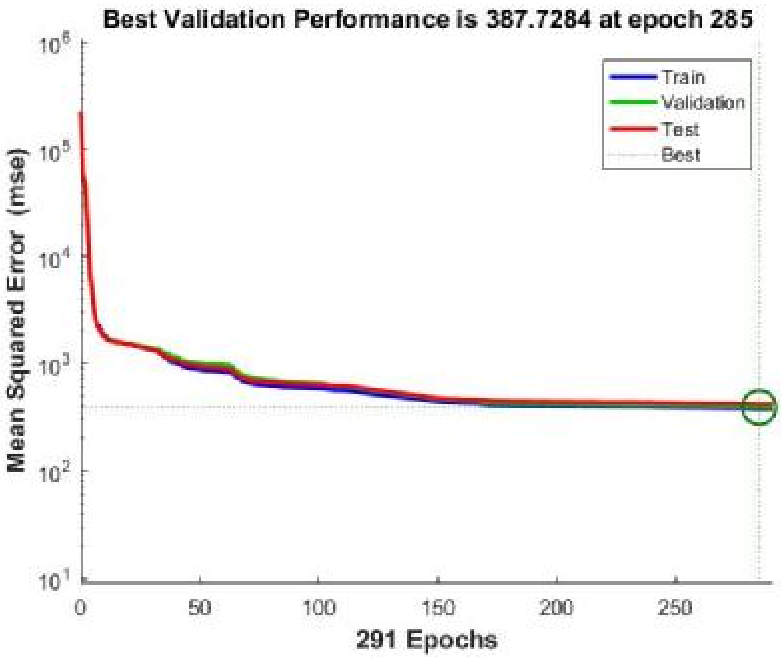

Figure 10: Performance of the Developed ANN

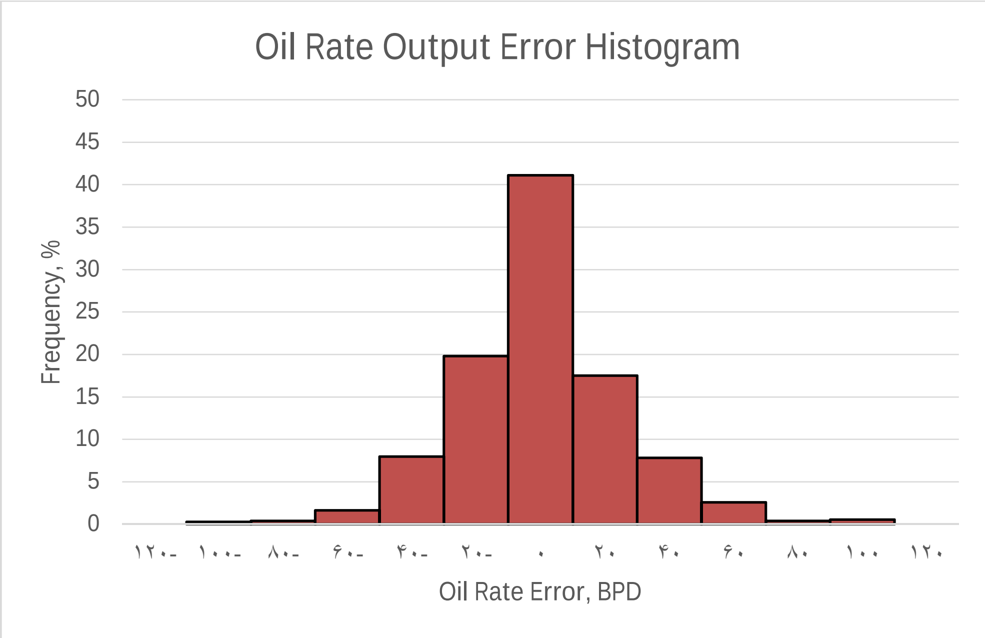

Figure 11: Error Histogram for Oil Rate Outputs of the Trained ANN

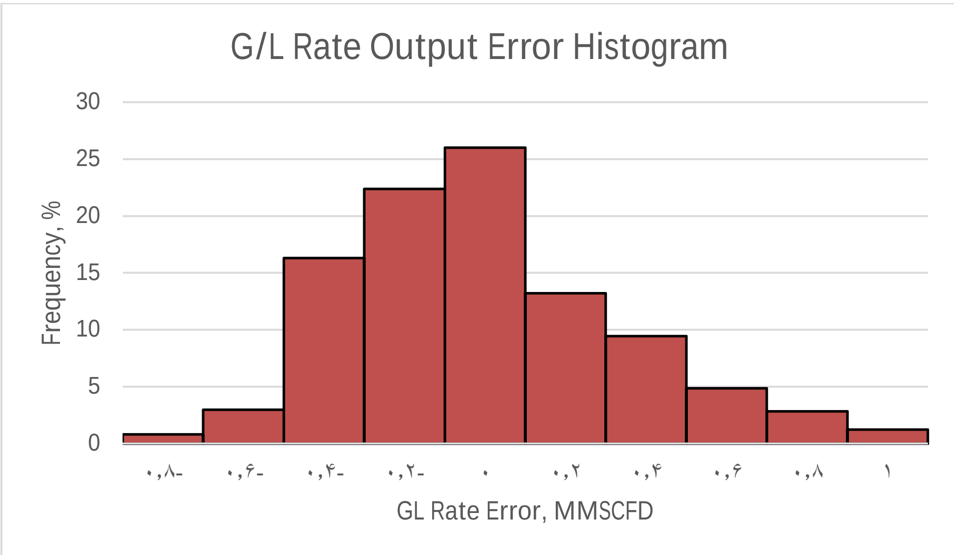

Figure 12: Error Histogram for G/L Rate Outputs of the Trained ANN

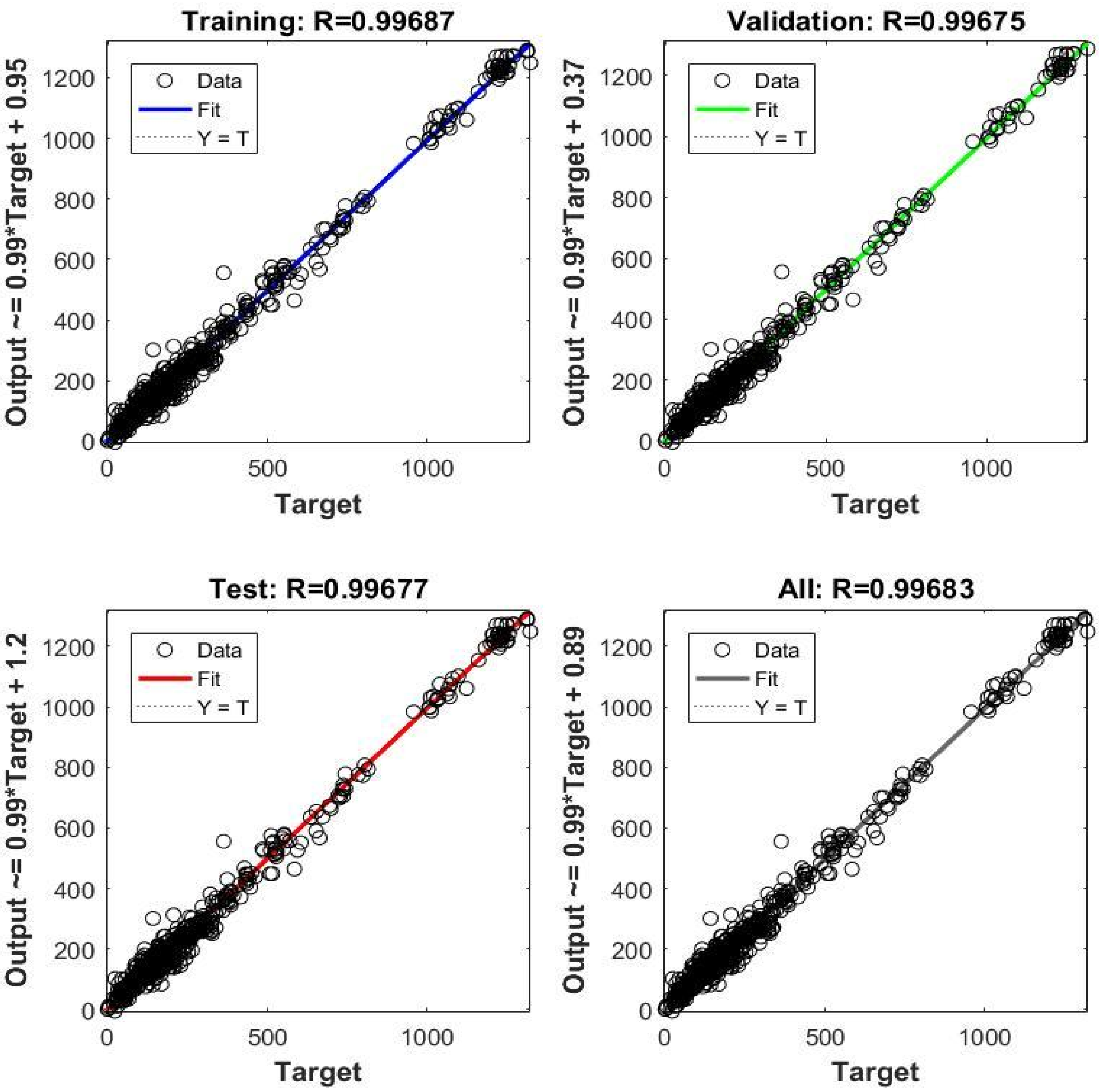

Figure 13: ANN Regression Curves (Predicted Outputs Versus Targets)

Testing the Trained Network

After performing the first test with the developed ANN model, 50 points were used as a secondary test for final approval of the model efficiency in predicting optimum oil rate and the optimum gas injection rate. These data are given in Tables 2 & 3. Figures 14 &15 show a good match between the predicted and measured oil rate and gas lift rate of the second test.

Table 2: Points Used as a Secondary Test for the Developed ANN Model

Parameter	Well Head Pressure (Psi)	Flow Line Pressure (Psi)	Flow Line Temperature (°c)	Separator Pressure (Psi)	Annulus Pressure (Psi)	Flow Line Length (m)	Choke Size, (1/64 in)	Water Cut (Percent)	Kick-off Point (m)	Inclination (°)	Gas Injection Depth (m)	Orifice Port size (in)	Reservoir Depth (m)	Net Pay Thickness (m)	Reservoir Pressure (Psi)
1	100	70	10	40	620	1484	64	0.7	2000	27	3152	0.125	3277	6	955
2	200	180	30	170	580	666	128	11	2400	26	2004	0.25	3387	1.5	3600
3	230	220	80	165	1020	4104	128	78.5	2000	36	1150	0.25	3585	9	4130
4	220	200	30	165	620	1558	128	30	2905	0	2886	0.25	2905	17	1277
5	70	50	30	40	750	3327	128	6	3510	0	2887	0.25	3510	25	1692
6	280	195	94	170	950	966	128	92	3616	0	1038	0.188	3616	4.5	4900
7	200	180	15	165	870	5166	128	1	2272	60	2702	0.125	3216	38	1853
8	230	195	34	170	500	4660	128	24	3038	0	2977	0.25	3038	12	2742
9	120	80	35	40	380	3160	64	1	3057	20	3406	0.188	3473	44	1200
10	430	420	44	380	1100	654	128	95	2303	29	833	0.25	3539	29	3655
11	300	250	15	170	1090	4911	128	26	2937	0	2828	0.188	2937	15	1578
12	105	100	20	40	870	2020	128	1	2009	61	3088	0.25	3121	20	1106
13	180	165	52	40	780	7906	128	38	2021	65	3125	0.5	3171	46	3000
14	55	45	30	40	380	1625	128	0.2	1935	60	3038	0.375	3158	13.5	3643
15	100	80	25	40	780	4742	128	1.8	2243	35	2736	0.313	2988	7	491
16	160	100	30	40	980	5086	128	0.2	3023	0	2805	0.188	3023	7.5	1600
17	120	90	10	40	650	11161	128	65	800	25	2848	0.188	3017	31	1421
18	85	75	130	40	900	1452	128	81	1800	28	2800	0.25	3077	8	2077
19	115	105	132	40	725	668	128	6	2000	30	2200	0.125	3200	10	1550
20	145	135	123	40	1074	4527	128	17	2015	35	1500	0.125	3540	9	1620
21	128	118	128	40	930	1568	128	6	3000	0	2700	0.125	3000	17	1282
22	93	83	126	40	1385	3357	128	6	3600	0	2900	0.125	3600	15	1720
23	110	100	130	40	1070	956	128	85	3700	0	2300	0.188	3700	7.5	2780
24	110	100	152	40	920	5186	128	29	2280	60	2500	0.25	3300	38	2310
25	115	105	165	40	1350	4650	128	90	3000	20	2977	0.25	3050	12	1920
26	163	153	130	40	924	3157	128	28	3057	20	3406	0.188	3473	44	1540
27	105	95	139	40	1150	685	128	63	2100	30	1500	0.125	3550	25	2700
28	140	130	100	40	1250	4851	128	53	2937	0	2828	0.188	2937	15	2730
29	160	150	160	40	1280	2058	128	23	2009	61	3088	0.25	3121	20	2700
30	130	120	120	40	773	7856	128	4	2021	65	3125	0.5	3171	46	1640
31	300	290	140	170	1250	1856	128	74	1935	60	3038	0.313	3158	13.5	3100

32	180	175	49	170	700	4865	128	92.3	360	0	326	0.313	360	15	1700
33	160	150	53	140	800	5008	128	95.3	351	0	330	0.375	351	20	1700
34	140	130	49	120	710	12846	128	93.9	357	0	326	0.188	357	16	800
35	255	242	31	229	720	1484	128	80.8	364	0	334	0.125	364	3	1100
36	140	130	51	123	760	666	128	92.6	380	0	325	0.25	380	5	800
37	170	160	54	150	940	7402	128	97.8	356	0	326	0.5	356	7	1700
38	230	220	49	210	330	1558	128	85	363	0	280	0.313	363	9	1700
39	140	130	54	120	750	3327	128	94.3	357	0	326	0.375	357	15	800
40	145	135	39	125	540	8240	128	91.5	375	0	327	0.188	375	2	800
41	180	170	27	160	260	5166	128	30	383	0	340	0.125	383	6	600
42	140	130	32	120	370	4660	128	89.1	363	0	336	0.25	363	8.5	650
43	160	150	52	140	920	3160	128	98.2	365	0	324	0.25	365	4.5	1700
44	155	145	52	135	700	568	128	93	380	0	325	0.125	380	10	800
45	130	120	29	100	400	4911	128	89.2	1129	0	331	0.25	1129	5	600
46	100	90	23	80	500	2057	128	73.3	1129	0	331	0.188	1129	15	600
47	102	92	26	82	370	7582	128	21	354	0	326	0.25	354	18	550
48	100	90	37	80	580	1625	128	76.7	366	0	321	0.125	366	20	1500
49	157	147	47	137	750	4742	128	92.3	380	0	325	0.188	380	7	800
50	180	170	32	160	280	5876	128	30.8	383	0	340	0.125	383	9	600

Table 3: Points Used as a Secondary Test for the Developed ANN Model (cont.)

Parameter	Reservoir Temperature (°f)	Bottom hole flowing Pressure (Psi)	Productivity Index (STB/Psi)	Reservoir Porosity (percent)	Reservoir Permeability (md)	Oil Gravity (API)	Formation Gas Oil Ratio (SCF/STB)	Gas Gravity	Oil Formation Volume Factor (RB/STB)	Oil Viscosity (cp)	Bubble Point Pressure (Psi)	Gas Formation Volume Factor (RB/MSCF)	Gas Viscosity (cp)	G/L Rate (MMSCFD)	Oil Rate (BPD)
1	280	457	0.18	12	1.4	33	10000	0.712	5	0.1	1765	3.18	0.01	1	67
2	200	971	0.09	11	2.6	41.8	1508	0.741	1.53	0.219	4987	0.946	0.02	1.5	136
3	266	3430	1.16	10	13	35	1266	0.714	1.67	0.234	4432	0.952	0.03	1.2	184
4	232	1060	1	16.5	13	30.4	250	0.814	1.2	0.453	1250	3.18	0.01	1.2	247
5	260	960	0.14	11	2.6	34.5	1508	0.741	1.2	0.312	4987	2.166	0.02	0.6	102
6	268	3800	2.91	10	13	45	1424	0.714	1.91	0.116	5511	0.852	0.03	1	194
7	259	1496	0.07	16.5	13	30	900	0.814	1.26	0.402	1250	2.071	0.02	1.7	87
8	260	990	0.09	16.5	13	27.4	897	0.814	1.34	0.253	4987	1.295	0.02	1	136
9	257	860	0.26	11	2.6	37.5	1508	0.741	1.2	0.312	4987	2.166	0.02	0	88
10	267	3500	2.6	10	13	30	1424	0.714	1.91	0.116	4432	0.852	0.03	1	40
11	241	1034	0.07	16.5	13	29	300	0.814	1.26	0.402	1250	2.071	0.02	1.5	81
12	232	511	0.16	16.5	13	32.4	300	0.814	1.2	0.453	1250	3.18	0.01	1	166
13	234	1341	0.64	16.5	13	29.7	1000	0.814	1.42	0.321	4405	1.018	0.02	1.2	437
14	240	549	0.05	16.5	13	33.8	240	0.814	1.49	0.306	4405	0.886	0.03	1.1	141
15	246	478	0.86	8	2.6	24	300	0.78	1.01	0.453	1032	3.18	0.01	1.2	194

16	211	562	0.19	16.5	13	28	605	0.814	1.31	0.321	4405	1.018	0.02	1.2	164
17	240	790	0.41	11	2.6	36	1508	0.761	1.36	0.34	1765	2.166	0.02	1.5	74
18	285	2030	1.66	12	1.4	32	359	0.712	2.58	0.1	1765	3.18	0.01	1.5	855
19	215	1543	2.82	11	2.6	40	359	0.741	1.53	0.219	4987	0.946	0.02	1.2	1833
20	265	1216	8.42	10	13	35	359	0.714	1.67	0.234	4432	0.952	0.03	1.5	1157
21	231	1200	5.91	16.5	13	31	359	0.814	1.2	0.458	1250	3.22	0.01	1.5	1500
22	250	1720	11.4	11	2.6	33	359	0.741	1.2	0.312	4987	2.166	0.02	0.9	1500
23	260	2660	2.59	10	13	44	279	0.714	1.91	0.168	5511	0.852	0.03	3.5	1716
24	240	1720	0.69	16.5	13	31	359	0.814	1.26	0.402	1250	2.071	0.02	1.2	1916
25	250	1920	5.18	16.5	13	28	359	0.814	1.34	0.258	4987	1.295	0.02	2.3	1875
26	260	1400	0.85	11	2.6	38	474	0.741	1.2	0.312	4987	2.166	0.02	2.2	800
27	260	2230	1.63	10	13	31	359	0.714	1.91	0.116	4432	0.852	0.03	2	1110
28	248	2300	1	16.5	13	30	164	0.814	1.26	0.402	1250	2.071	0.02	2.6	614
29	235	2276	1.35	16.5	13	33	164	0.814	1.2	0.453	1250	3.18	0.01	2.5	715
30	220	1484	2.98	16.5	13	30	164	0.814	1.58	0.321	4405	1.018	0.02	1.5	1411
31	240	2570	7.26	16.5	13	32	819	0.814	1.49	0.306	4405	0.886	0.03	2.1	1690
32	155	942	1.64	23	700	25	1000	0.814	1.42	0.321	1035	3.18	0.01	1	94
33	152	1020	2.63	25	700	26	240	0.814	1.49	0.306	1035	1.018	0.02	1.5	82
34	130	680	8.24	11	80	35	300	0.778	1.01	0.453	1035	0.886	0.03	1.2	59
35	154	1078	6.91	21	40	37	605	0.814	1.31	0.321	1035	3.18	0.01	1.2	28
36	130	670	11.5	25	180	40	1508	0.761	1.36	0.345	1035	1.018	0.02	0.6	108
37	155	1179	2.49	12	600	36	359	0.712	1.57	0.15	1035	2.166	0.02	1	28
38	155	1153	0.64	22	900	31	359	0.741	1.53	0.219	1035	3.18	0.01	1.7	52
39	130	680	8.68	11	80	35	359	0.714	1.67	0.234	1035	0.946	0.02	1	58
40	130	375	1.06	20	100	41	359	0.814	1.2	0.453	1035	0.952	0.03	0.9	38
41	154	374	0.2	19	20	31	359	0.741	1.2	0.312	1035	3.18	0.01	1	31
42	156	441	0.28	21	60	29	279	0.714	1.85	0.118	1035	2.166	0.02	1.5	66
43	155	1100	3.23	21	500	36	359	0.814	1.26	0.402	1035	0.852	0.03	1	34
44	130	670	12.6	25	180	35	359	0.814	1.34	0.253	1035	2.071	0.02	1.2	113
45	158	565	6.77	22	80	28	474	0.741	1.2	0.316	89.2	1.296	0.02	1.1	26
46	158	565	1.8	22	80	31	359	0.714	1.91	0.116	73.3	2.166	0.02	1.2	17
47	154	249	0.51	23	300	29	164	0.814	1.26	0.402	1035	0.855	0.03	1.2	120
48	155	660	0.19	23	400	32	164	0.814	1.36	0.453	1035	2.071	0.02	1.5	36
49	130	670	10.8	25	180	28	164	0.814	1.42	0.321	1035	3.15	0.01	1.5	106
50	154	374	0.21	19	20	27	819	0.814	1.49	0.306	1035	1.018	0.02	1.2	33

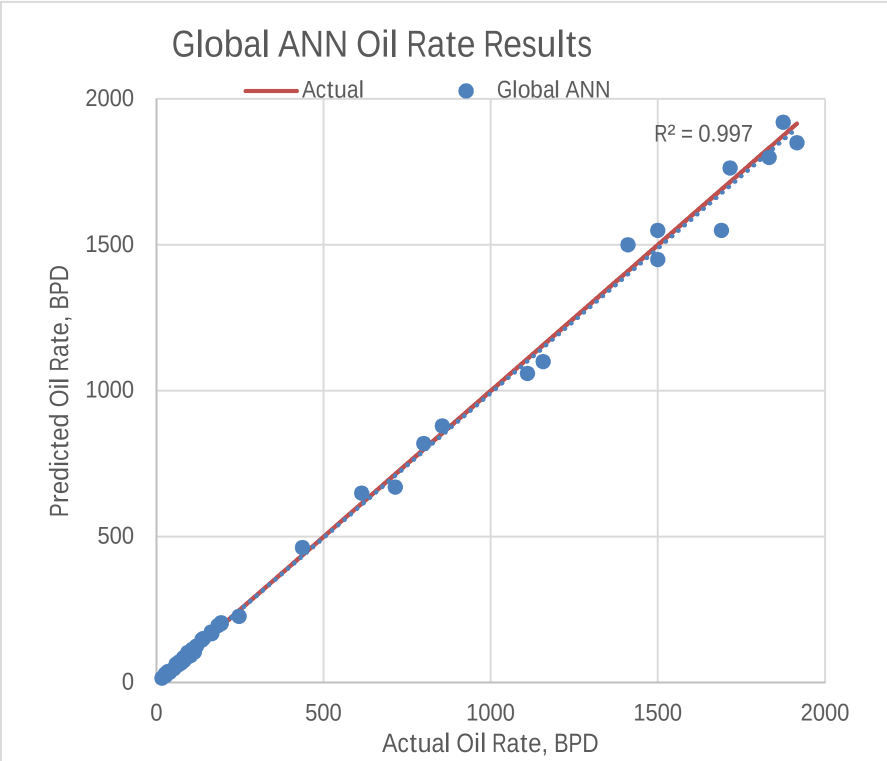

Figure 14: Actual vs Predicted ANN Oil Rate

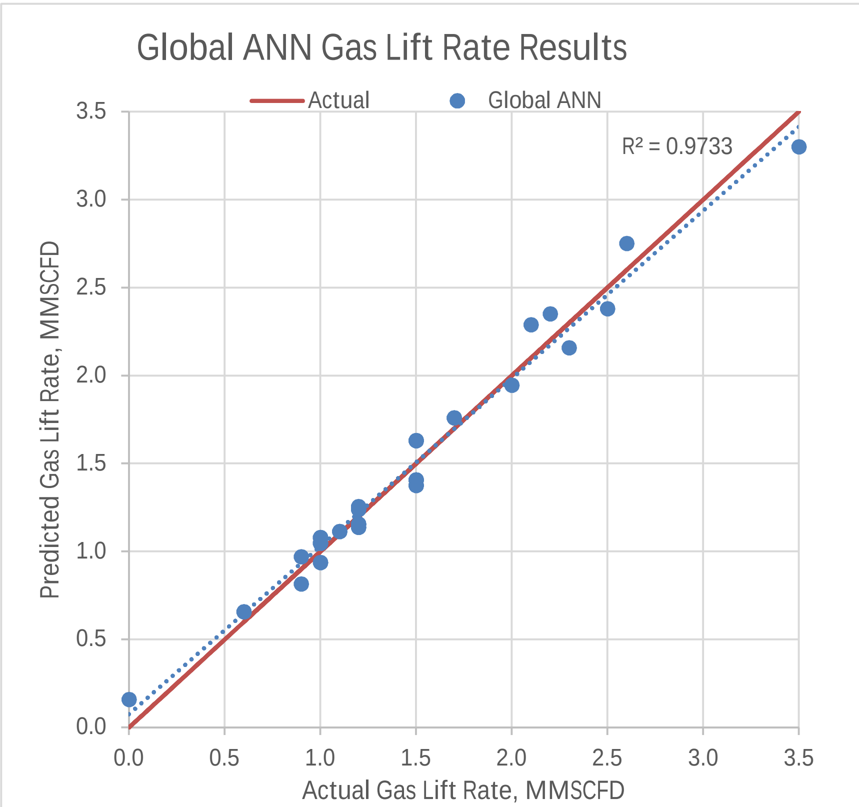

Figure 15: Actual vs Predicted ANN GL Rate

Well by Well ANN Models

Because wells respond in different manners to G/L parameters variation and reservoir pressure depletion, the researcher proposed a new strategy for ANN, which is to develop a neural network for each well independently on other wells test data, thus enhancing the predicted parameters and minimizing the error. Each code of these independent codes gives oil rate and G/L rate for a single well. Figures 16 & 17 display the results of this method.

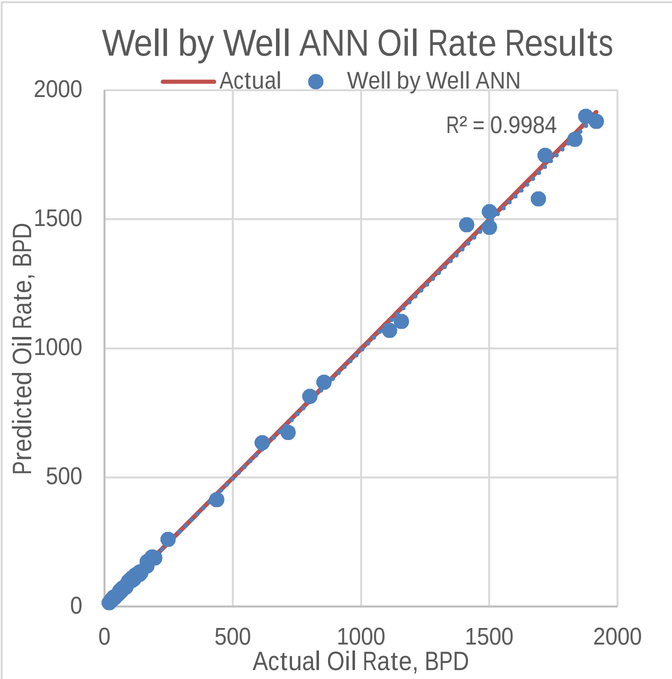

Figure 16: Actual vs Predicted Well by Well ANNs Oil Rate

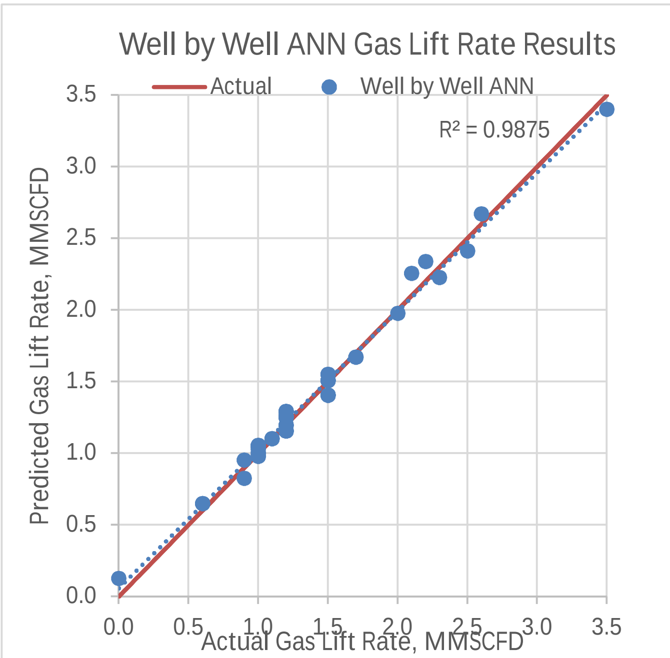

Figure 17: Actual vs Predicted Well by Well ANNs GL Rate

Comparative Analysis and Discussion

Obtained results by using global ANN and well by well ANNs were compared with the results obtained from Pipesim software. Figures 18 &19 display the results of these methods for oil rate and gas lift rate respectively. It can be noticed from these figures that the Well by Well ANN models' results are closest to the actual data and Pipesim results are the furthest to the actual data.

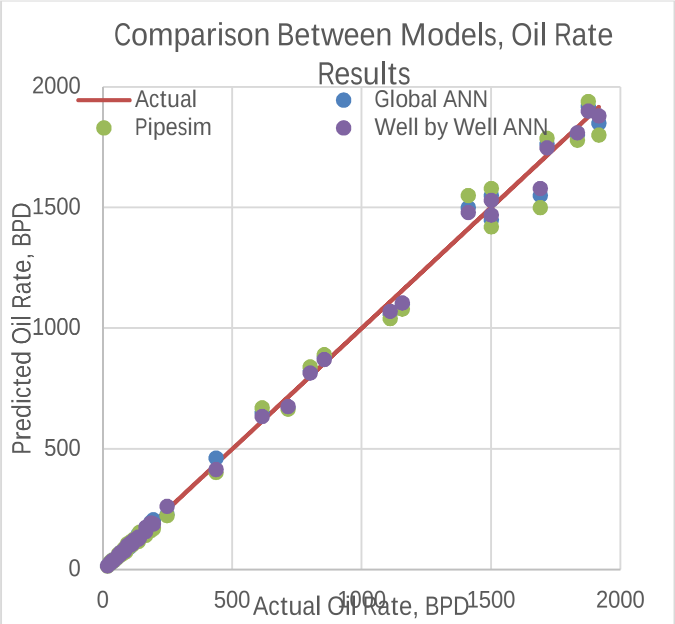

Figure 18: Comparison Between Models in Oil Rate Results

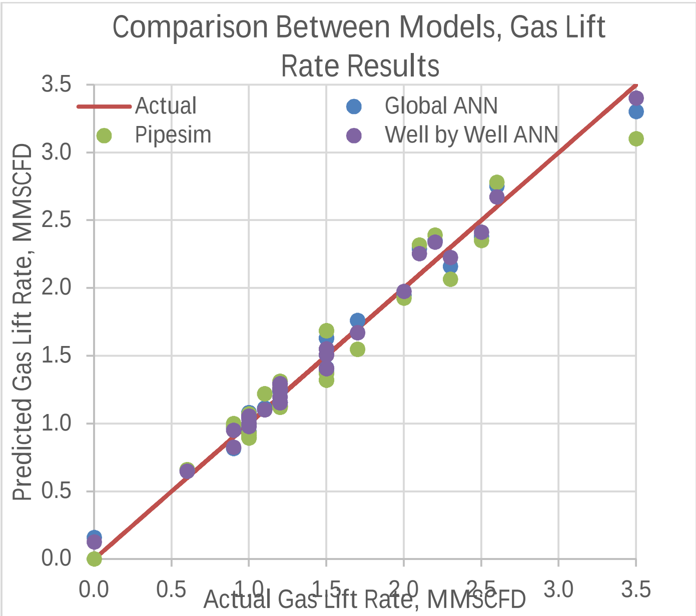

Figure 19: Comparison Between Models in

Tables 4 & 5 show the statistical analysis of these three methods for oil rate results and gas lift rate results respectively. This analysis used to evaluate the results of these method based on Average Percent Relative Error (APRE), Average Absolute Percent Relative Error (AAPRE), Minimum Percent Relative Error (Min PRE), Maximum Percent Relative Error

(Max PRE), Root Mean Squared Error (RMSE), Mean Squared Error (MSE), Correlation Coefficient Squared (R^2), Correlation Coefficient (R) and Error Standard Deviation (SD).

As can be seen from Tables 4 & 5, Well by Well models produce the most accurate results, as they depict the lowest APRE, AAPRE, MSE, RMSE & SD, and Highest R^2 & R, which means the error of this method is the closest to zero error, on contrary Pipesim models produce the least accurate results as they depict the highest APRE, AAPRE, MSE, RMSE & SD, and lowest R^2 & R, which means the error of this method is the furthest to zero error.

Table 4: Statistical Analysis of Oil Rate Result

Parameter	Pipesim	Global ANN	Well by Well ANN
APRE, %	-1.9	0.6	-0.3
AAPRE, %	9.0	6.3	3.8
Min. PRE%	-14.9	-11.1	-7.4
Max. PRE%	13.8	10.6	6.4
RMSE	49	33	25
MSE	2375	1098	606
R^2	0.994	0.997	0.998
R	0.997	0.999	0.999
SD	48	33	24

Table 5: Statistical Analysis of Gas Lift Rate Results

Parameter	Pipesim	Global ANN	Well by Well ANN
APRE, %	-1.9	1.3	1.2
AAPRE, %	8.6	5.7	3.8
Min. PRE%	-12.0	-9.4	-8.4
Max. PRE%	12.3	9.6	8.0
RMSE	0.136	0.093	0.065
MSE	0.018	0.009	0.004
R^2	0.945	0.973	0.987
R	0.972	0.987	0.994
SD	0.132	0.092	0.064

The Percentage Relative Error (PRE) was calculated for Pipesim, global ANN model, well by well ANN models results for oil rate and G/L rate in Figures 20 & 21 respectively. From Percent Relative Error histograms, well by well ANN model has the lowest Max. PRE and the highest Min. PRE, thus the lowest range of error (11.2 % & 12.2 % for oil rate and G/L rate respectively). Pipesim model has the highest Max. PRE and the lowest Min. PRE, thus the highest range of error (23.9 % & 20.6 % for oil rate and G/L rate respectively).

Relative Importance of Input Variables in the Developed ANN Models

The weights connecting the variables in the neural network can be used to determine the relationships between variables. The weights indicate the relative effect of information refined in the network. Input variables that are not relevant to an output variable are inhibited by their weights. The opposite effect can be noticed for weights given to variables that have strong direct or reverse relations with an output variable.

A method proposed by Garson 1991 indicates the relative importance of input variables for a single output variable in the neural network by partitioning the model weights. The relative importance of a variable can be determined by identifying all weights connecting the specific input node that move through the hidden layer to the output variable. This is repeated for all other variables until a list of all weights that are related to each input variable is obtained. The connections are listed for each input node and scaled relative to all other inputs. A single value is obtained for each variable that describes the relationship with the response variable in the model. The equation of Garson algorithm to determine the relative importance of input variables is given by:

$$IM(X_p) = \frac{\sum_{j=1}^{n_h}\left[\left(|I|_{p_j} \Big/ \sum_{k=1}^{n_p}|I|_{p_{j,k}}\right)|O_j|\right]}{\sum_{K=1}^{n_p}\left\{\sum_{j=1}^{n_h}\left[\left(|I|_{p_{j,k}} \Big/ \sum_{k=1}^{n_p}|I|_{p_{j,k}}\right)|O_j|\right]\right\}} \qquad (2)$$

Where:

$IM(X_p)$ represents the percentage of importance of the input variable on the output variable. n_p is the number of input variables and n_h is the number of neurons in the hidden layer, the term $|I|_{p_{j,k}}$ is the absolute value of the weight of the kth input variable in the Jth hidden layer. The term $|O_j|$ is the absolute value of the output layer weight in the neural network for Jth hidden layer.

Tables 6 & 7 list the relative importance of various input parameters on both oil rate output and gas lift rate output respectively. As can be generally seen, water cut has the greatest impact on oil rate and gas lift rate prediction followed by net pay thickness (or producing interval), most of the parameters have almost equal importance in the range of (5%-3%), separator pressure and flowline temperature have the least impact on the output parameters in the developed ANN model.

The results of Garson calculation can be summarized as follows:

- Water cut has the greatest importance on both oil rate and G/L rate. As water cut increases in a well, the total pressure gradient in the well will increase because of the increase in liquid density as water is heavier than oil, thus causes a decrease in oil rate and necessitates increasing gas lift rate to bring oil production rate to its previous value.
- Net pay thickness comes in second place in importance. As the net pay thickness increases, the flow area increases, which allows producing more liquid amount from the reservoir, this requires injecting more amount of gas lift to bring GLR to its former value.
- Other parameters related to reservoir fluid properties and wellbore performance affect almost equally on both oil rate and G/L rate.
- Separator pressure and flow line temperature have insignificant influence on both oil rate and G/L rate, so they can be neglected in ANN models.

Based on inputs’ relative importance, ANN model was reconstructed after excluding the least 5, 10, 15, 20 & 25 important input parameters, and models were compared to the original model using R, MSE, error SD, APRE and AAPRE. As in Table 8 & Figure 22, R-values were not affected significantly due to data accuracy and abundance. On the other hand, other statistical parameters showed increase as the number of inputs decreased as in Figures 23 & 24, due to the loss of importance of data excluded from the models, which decreases the model efficiency to get accurate results.

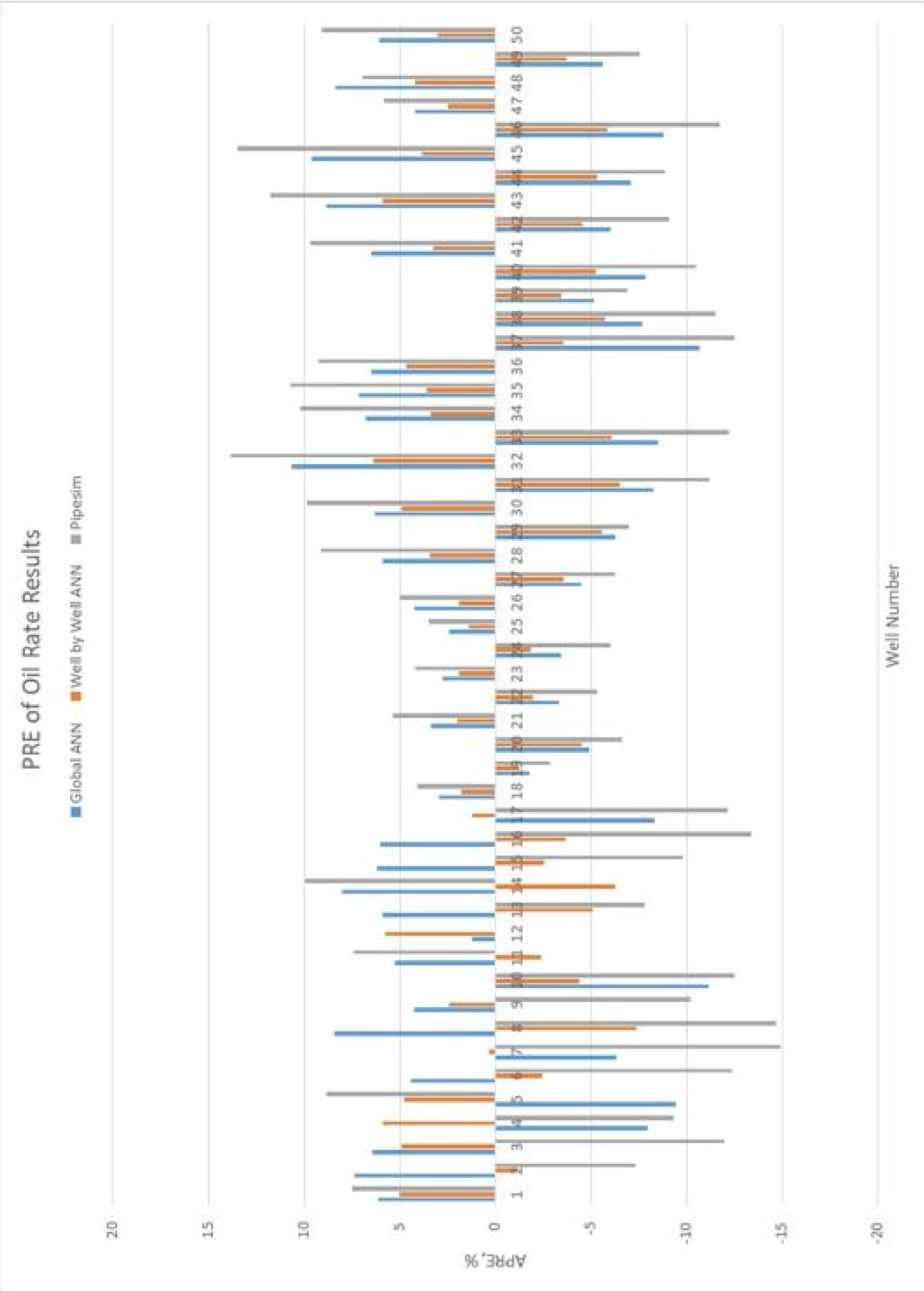

Figure 20: Percent Relative Error for Oil Rate Test Results

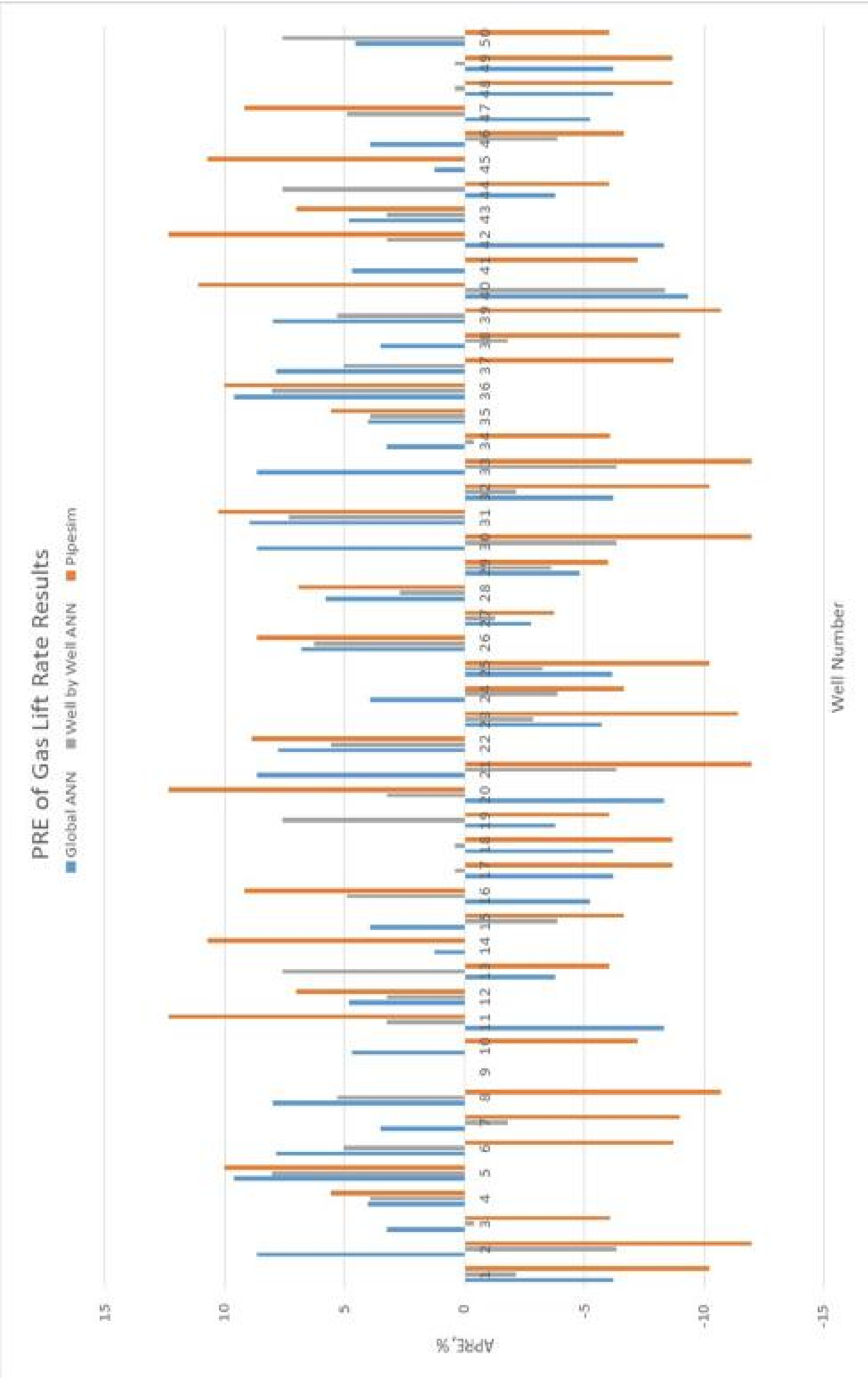

Figure 21: Percent Relative Error for Gas Lift Rate Test Results

Table 6: Relative Importance of Input Parameters on Oil Rate Output.

Parameter	Relative Importance %	Parameter	Relative Importance %
Water Cut	8.10	Gas Gravity	3.29
Net Pay Thickness	5.04	Reservoir Permeability	3.27
Reservoir Temperature	4.74	Oil Formation Volume Factor	3.24
Orifice Port Size	4.73	Kick-off Point	3.10
Inclination	4.67	Oil Gravity (API)	3.09
Bottom Hole Flowing Pressure	4.50	Gas Viscosity	3.04
Gas Injection Depth	4.30	Flow Line Pressure	2.91
Flow Line Length	4.27	Reservoir Porosity	2.84
Gas Formation Volume Factor	3.99	Annulus Pressure	2.82
Choke Size	3.96	Reservoir Pressure	2.81
Productivity Index	3.71	Formation Gas-Liquid Ratio	2.81
Oil Viscosity	3.69	Well Head Pressure	2.60
Reservoir Depth	3.42	Separator Pressure	2.21
Bubble Point Pressure	3.29	Flow Line Temperature	1.64

Table 7: Relative Importance of Input Parameters on Gas Lift Rate Output

Parameter	Relative Importance %	Parameter	Relative Importance %
Water Cut	7.45	Choke Size	3.29
Net Pay Thickness	6.58	Bubble Point Pressure	3.17
Orifice Port Size	5.60	Oil Gravity (API)	3.01
Reservoir Temperature	4.86	Oil Formation Volume Factor	2.97
Gas Injection Depth	4.74	Gas Gravity	2.94
Flow Line Length	4.45	Annulus Pressure	2.78
Oil Viscosity	4.20	Reservoir Porosity	2.74
Gas Viscosity	4.17	Reservoir Depth	2.62
Productivity Index	4.14	Kick-off Point	2.49
Bottom Hole Flowing Pressure	3.97	Reservoir Pressure	2.42
Flow Line Pressure	3.60	Formation Gas-Liquid Ratio	2.22
Inclination	3.52	Well Head Pressure	2.08
Reservoir Permeability	3.48	Separator Pressure	1.70
Gas Formation Volume Factor	3.40	Flow Line Temperature	1.42

Table 8: Effect of Number of Inputs on Model Statistical Parameters

No. of Inputs	No. of Excluded inputs	Inputs Total Importance %	Correlation Coefficient (R)				MSE	SD	APRE %	AAPRE %
			Training R	Validation R	Testing R	All R				
3	25	19	0.97608	0.97625	0.97522	0.97598	3060	54.6	-22.7	40.4
8	20	41	0.98405	0.98172	0.98332	0.9836	2014	43.9	-15.5	29.4
13	15	60	0.98837	0.98724	0.98862	0.98825	1432	36.3	-12.2	24.6
18	10	75	0.9924	0.99357	0.99275	0.99263	1109	29.5	-7	17.9
23	5	90	0.99379	0.9932	0.99336	0.99364	873	27.3	-5.7	16.9
28	0	100	0.99687	0.99675	0.99677	0.99683	388	24.1	-4.9	14.7

The cut off number of inputs is the number of inputs after which, further decrease in number of inputs causes significant decrease in correlation coefficient values and a significant increase in MSE, SD, APRE & AAPRE, which decreases the model accuracy. Also, increasing the number of inputs more than this optimum number, causes a slight increase in correlation coefficient values and insignificant decrease in MSE, SD, APRE & AAPRE, this effect on increasing model accuracy can be neglected and stop further increasing the number of inputs. This can be indicated by a decrease in statistical parameters trendline slopes, the curves tend to be more horizontal, which causes insignificant change in their value with the increase in the number of inputs, as shown in Figures 22, 23 & 24 the cut off number of inputs is 18 inputs which corresponds to 75% total importance.

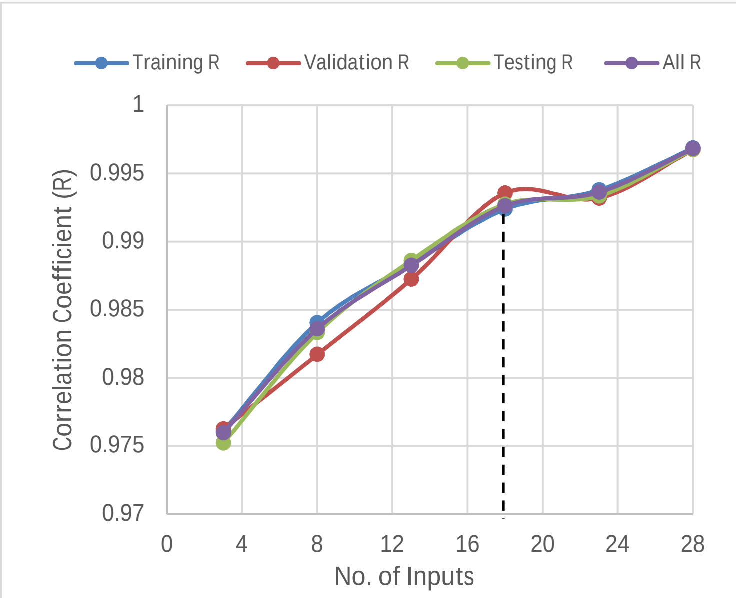

Figure 22: Correlation Coefficients of the Reduced Models

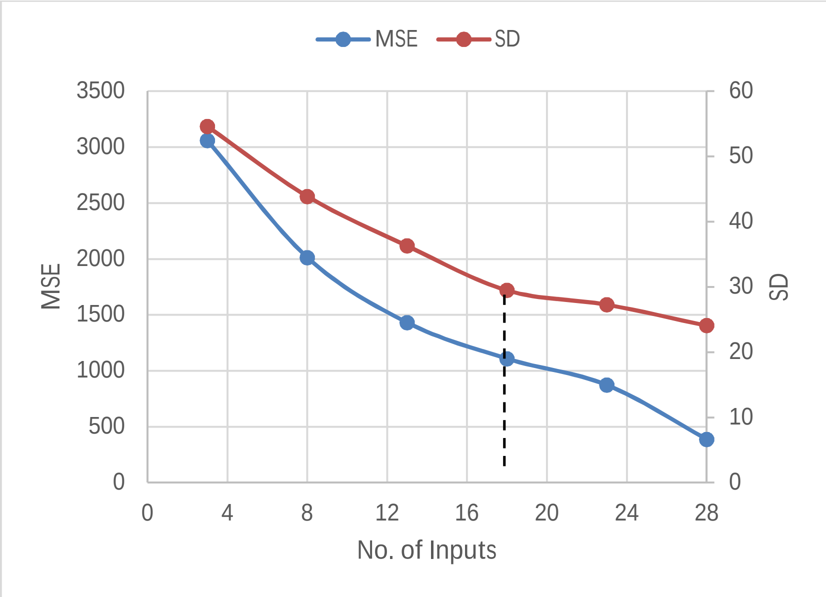

Figure 23: MSE & SD of the Reduced Models

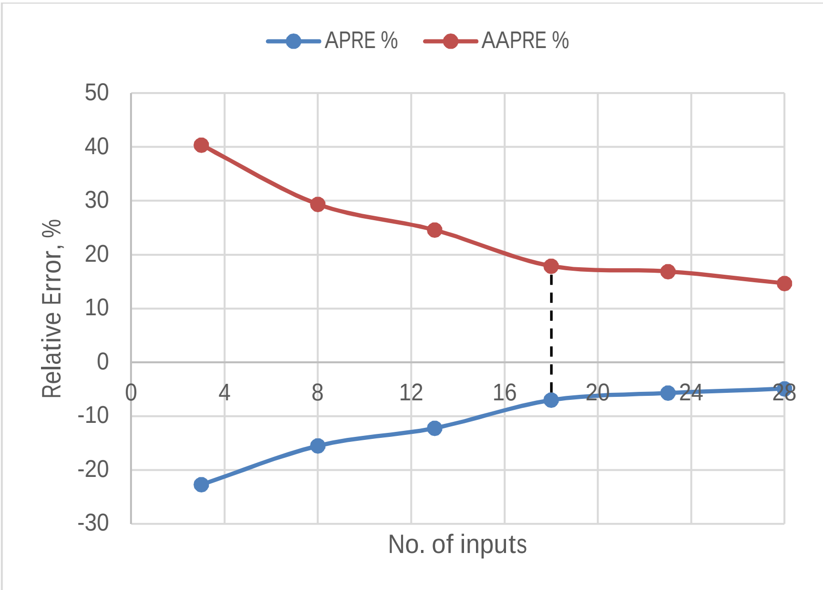

Figure 24: APRE & AAPRE of the Reduced Models.

Comparison with Previous Work

Ranjan *et al*., (2015) used ANN for Gas Lift Optimization. Their study is based on wells in India which are under gas lift operations. They used 10 input parameters for the ANN model to predict 2 output parameters (oil rate & gas lift rate). Figure 25 compares training, validation and testing data regression of Ranjan *et al* and our study. It can be seen that our study regression is greater than Ranjan *et al*, thus our study model is more accurate due to the great number of inputs included in this study.

Shokir *et al*., (2017) used synthetic sample points of 7 input variables for the ANN model to obtain oil rate as output, Figure 26 shows a comparison between test data regression of Shokir *et al* and our study. It can be concluded that our study is more accurate (greater regression) as it uses actual data of larger input data set.

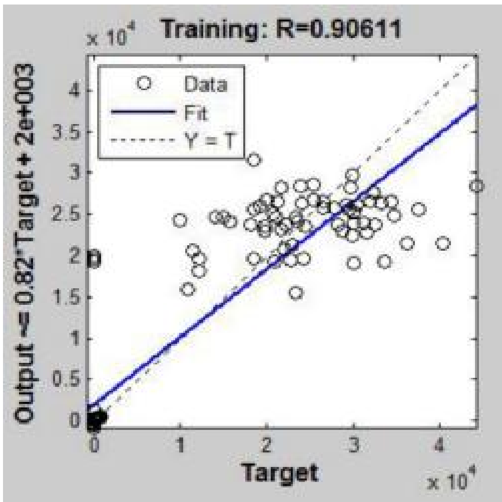

Figure (25.a): Ranjan *et al* Training Data Regression

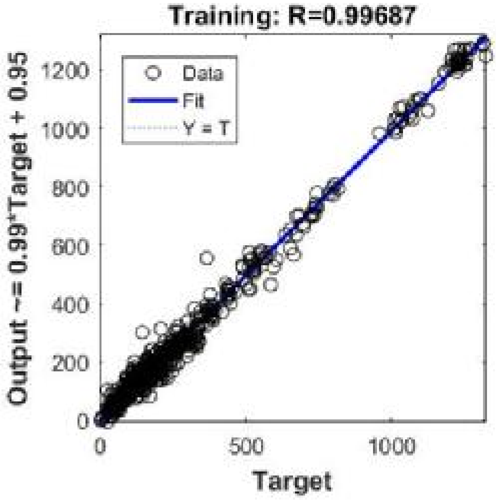

Figure (25.b): Study Training Data Regression

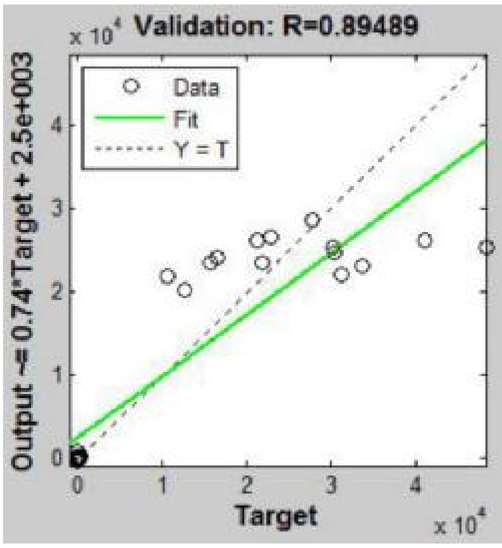

Figure (25.c): Ranjan *et al* Validation Data Regression

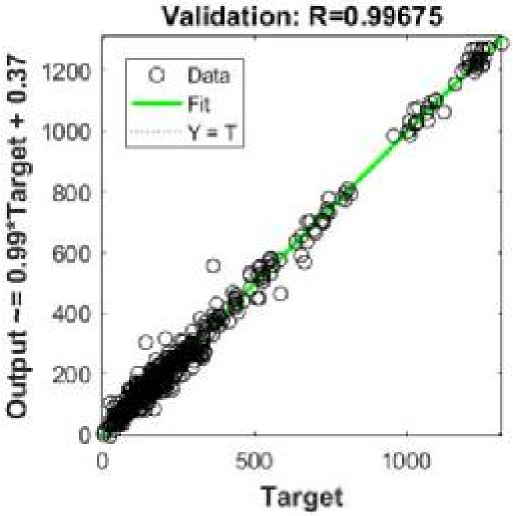

Figure (25.d): Study Validation Data Regression

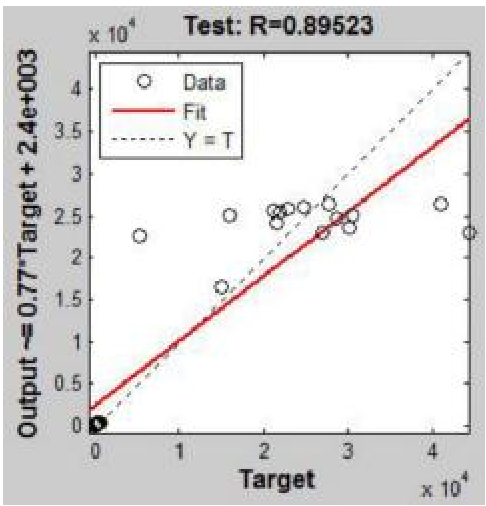

Figure (25.e): Ranjan *et al* Test Data Regression

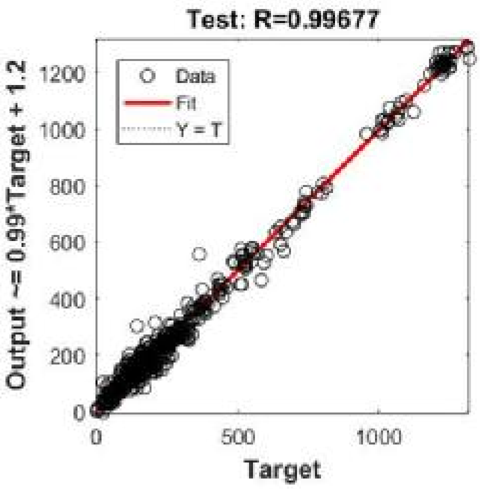

Figure (25.f): Study Test Data Regression

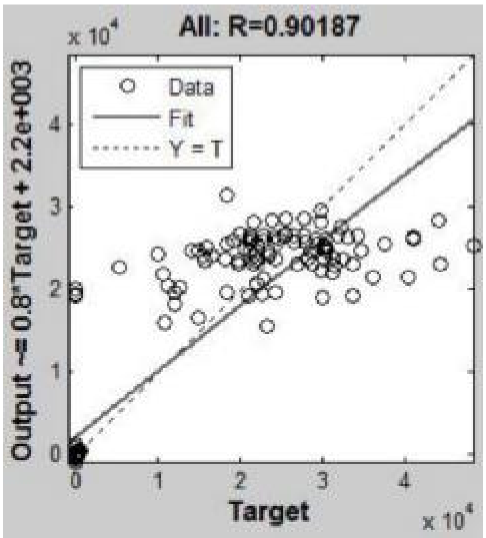

Figure (25.g): Ranjan *et al* All Data Regression

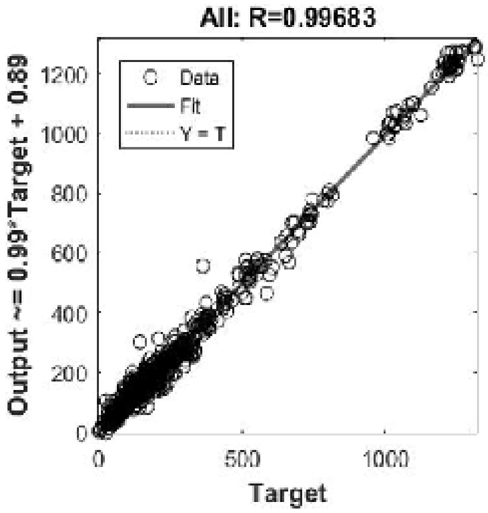

Figure (25.h): Study All Data Regression

Figure (25): Comparison between Ranjan *et al* and Study Input Data Regression

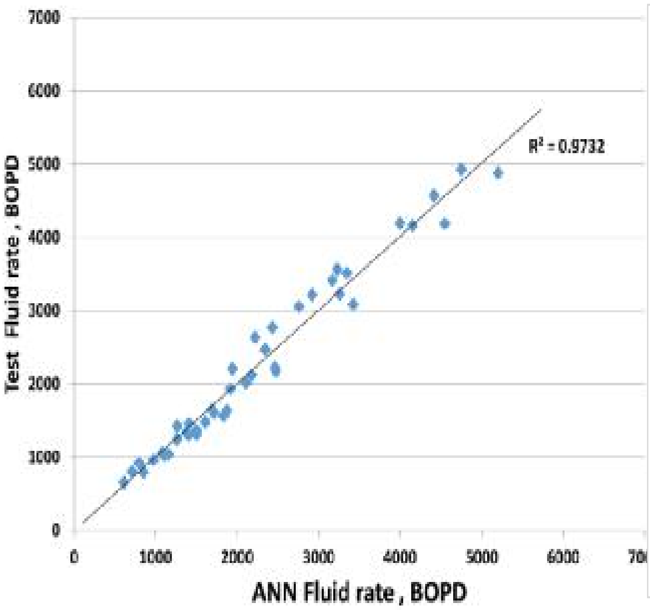

Figure (26.a): Shokir *et al* Test Data Regression

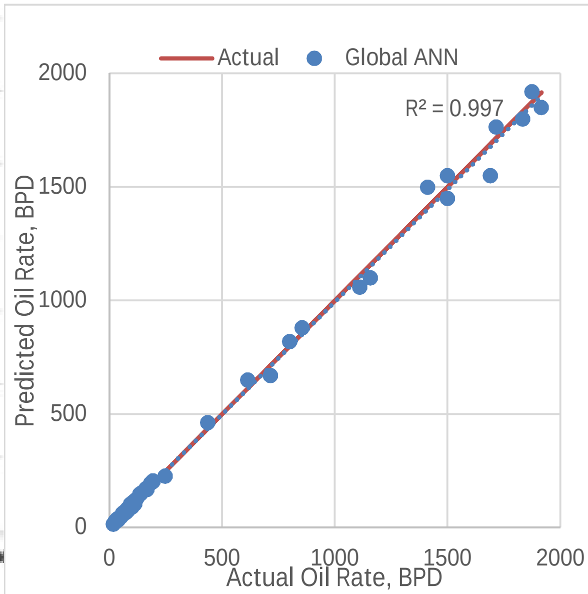

Figure (26.b): Study Test Data Regression

Figure (26): Comparison between Shokir *et al* and Study Test Data Regression

Conclusions and Recommendations

In this paper, various models were presented to predict gas lift optimization parameters (optimum oil rate and optimum gas lift injection rate): Pipesim models that use conventional nodal analysis and ANN models that use wells' history and databases.

A global ANN model for the entire wells was developed, trained for optimum structures, and tested using wells' test data. Also, single well ANN models were presented to predict the optimization parameters for each well separately.

Statistical analysis has been performed and showed that Global ANN model and Well by Well ANN models produce more accurate results than Pipesim models.

The influence of input parameters on output parameters has been calculated using Garson algorithm, and the least important input data were excluded to obtain reduced ANN models with only the most important inputs. The reduced models were constructed, run and evaluated against the inclusive model.

It has been shown that there is a cut off number of inputs required to gat accurate model and any further decrease in input number would decrease correlation coefficient value and increase mean squared error, error standard deviation and relative error, affecting model accuracy adversely.

A comparison with previous studies showed that this study presents more accurate results because a larger accurate data set of more input parameters were incorporated.

The concluded that ANN is a powerful, simple, trustful tool that provides an alternative for complex calculations of the nodal analysis and hence speeds up the calculations and saves effort and time, also ANN can handle incomplete and faulty information.

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