Prediction of Gas Lift Parameters Using Artificial Neural Networks

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Abstract
The purpose of this study has been the assessment of capability of Artificial Neural Networks in Gas Lift Operations optimization, which is in use for improved oil recovery from oil wells. This, in detail, is in fact an estimation of the two most important parameters of the process, i.e. optimal injection depth and optimal gas injection rate. In oil producing wells, if the bottom hole flowing pressure is smaller than the tubing pressure loss caused by a fluid with a given flowing gradient, then gas lift may be employed. For gas lift, gas is injected continuously or intermittently at selected location(s), resulting in a reduction in the natural flowing gradient of the reservoir fluid, and thus reducing the hydrostatic component of the pressure drop from the bottom to the top of the well. Artificial Neural Network has been well-vtilized very well for engineering applications during the past two decades. In this article two models are presented for prediction and optimization of both the optimal injection depth and gas injection rate, using this methodology. For this purpose four-layer neural networks have been designed and trained using real data from 36 wells. After the training step, four real data were also used for the model test step and as a reliability check. The outputs of models for test data are compared with the Commercial Package-EPS v3.6d software analysis. It has been concluded that Artificial Neural Networks approach has an excellent competing capability for this purpose compared to conventional methods and can be used interchangeably. This methodology and design can significantly help in the prompt optimal design of gas lift operations. The use of ANNs for applied problems is not a new subject by itself. However, its successful application to any specific problem can be considered as a novelty when proposed for the first time. This appears to be the first report of applying ANNs to continuous gas lift optimization problem.

Keywords: Gas Lift Optimization, Injection Depth, Water Cut, Injection Pressure, Neural Networks

1. Introduction

Artificial lift is used in oil production when the energy of the reservoir is not enough to sustain the flow of oil in the well up to the surface with satisfactory economic return. Selection of the proper artificial lift method is critical to the long-term profitability of an oil well; a poor choice will lead to low production and high operating costs. There is very little margin for error when one is designing lift systems for oil fields. There is a strong need for reliable procedures of selection and design. Therefore, computer programs that simulate the operation of lift systems are an important part of such procedures [1]. An extensive overview of artificial lift design considerations is presented in [2].

Rod pumps, electric submersible pumps and gas lift are the most common artificial lift systems, but plunger lift, hydraulic and progressing cavity pumps are also used.

Gas lift is a widely used method among artificial lift methods, in which gas is injected in the production well providing energy to the flow. Continuous gas lift being cost effective, easy to implement, very effective in a wide range of operating conditions and requiring less maintenance in comparison to other alternatives, is one of the most typical forms of artificial lift in oil production. It is a usual one where there is an abundance of natural gas resources [3].

The basic principle consists of decreasing the pressure gradient in the liquid via the injected gas (Fig. 1). The resulting mixture becomes less heavy than the original oil so that it eventually starts flowing, [4] and [5] for further understanding of the mechanisms, also Fig. 2 [6].

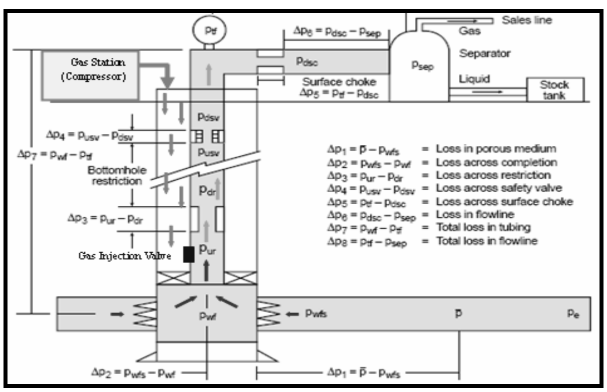


Figure 1. Schematic of a gas lift well

In gas lift operations, two problems are especially important. The first is finding the optimal position for injection point and the other is estimating the optimal gas injection rate.

In the present study, the data of 40 wells that are under gas lift operation were used. These wells were selected from one of the huge oil reservoirs in southwestern Iran. This reservoir has more than 150 wells, a portion of which are producing under a gas lift system. For each of these wells, the following set of data were gathered for subsequent use in the study: Bottom Hole Static Pressure (BHSP), Well Head Flowing Pressure (WHFP), Bottom Hole Flowing Pressure (BHFP), Productivity Index(PI), Well-Bore Size, Tubing Size, Water-Cut Percent(WC%), Oil Production Rate(Q_{Oil}), Gas Injection Rate (Q_{GasInj}) and Depth of Injection. The range of data is given in Table 1. The last two variables are considered as output data and the others as input data. Though Gas Oil ratio (GOR) is also a role-playing parameter, since the considered reservoir is an under-saturated, spatially well-communicating one, GOR is the same for all wells and therefore is not taken as a variable here.

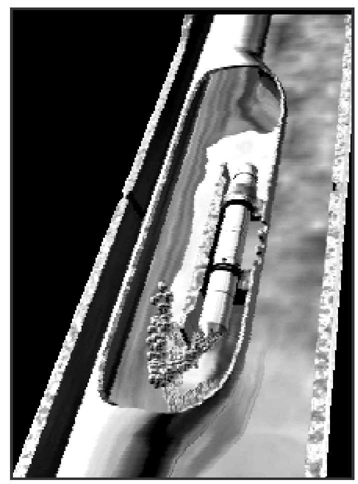


Figure 2. Enlarged view of a typical gas injection valve

Table 1. Range of training data

	Parameters	Min	Max
Input Data	BHSP (psi)	4300	5933
	WHFP (psi)	411	670
	BHFP (psi)	4157	5300
	PI	0.43	3.56
	Well-Bore Size (in)	5"	7"
	Tubing Size (in)	3 1/2"	6 1/8"
	WC%	0	2
	Q_{oil} (STB/day)	200	3200
	Well Depth (ft Drilled Depth)	11508	13650
Output Data	Q_{GasInj} (MMSCFD)	0.9	3.2
	Injection Depth (ft)	8090	10988

The two aforementioned crucial factors of the design are conventionally usually estimated through the use of multiphase flow simulation packages available in the market, and are subsequently implemented in a field scale plan. Neural Network-based models seem to be one of the newest tools finding their way into the oil and gas industry as an alternative analytical method [7]. For well flow performances there have already been some attempts regarding the temperature profile predicttion using neural networks [8]. In the present study, this approach has been applied to gas lift optimization, through predicting the two most important parameters of the design as described above.

It should be mentioned that due to the industrial scale of the events, data availability is usually choked by confidentiality limitations.

2. Optimizing gas lift for individual wells

Gas lift is a costly, however indispensable means to recover oil from high-depth reservoirs that entails solving the gas-lift optimization problem (GOP), often in response to variations in the dynamics of the reservoir and economic oscillations [9].

As the relative oil and gas superficial velocities in a pipe vary the flow regime in the pipe changes according to some empirical vertical flow pattern maps (For example see [10] and [11]) we avoid entering the slug regime area. If you take a well under tubing head pressure control and gradually increase the supply of lift gas to it, the production rate at first increases due to the reduced density of the mixture in the tubing. But as the lift gas supply is increased further, friction pressure losses in the tubing become more important, and the production rate starts the decline, (Fig. 3). For an individual well with no constraints other than a tubing head pressure limit, with an unlimited free supply of lift gas, the optimum lift gas injection rate is the value at the peak (point A).

In reality of course, lift gas is never free. Compression costs can be expressed as a cost per unit rate of lift gas injection (for example, dollars/day per MMscf/day). This must be balanced against the value of the extra amount of oil produced. Thus there is a "minimum economic gradient" of oil production rate versus lift gas injection rate, at which the value of the extra amount of oil produced by a small increase in the lift gas injection rate is equal to the cost of supplying the extra amount of lift gas. The optimum lift gas injection rate is then somewhat lower than the peak value at the point on the curve where its gradient equals the minimum economic gradient (point B). However in this study we assumed that gas supply is unlimited and free-source, and therefore we have tried to obtain point A.

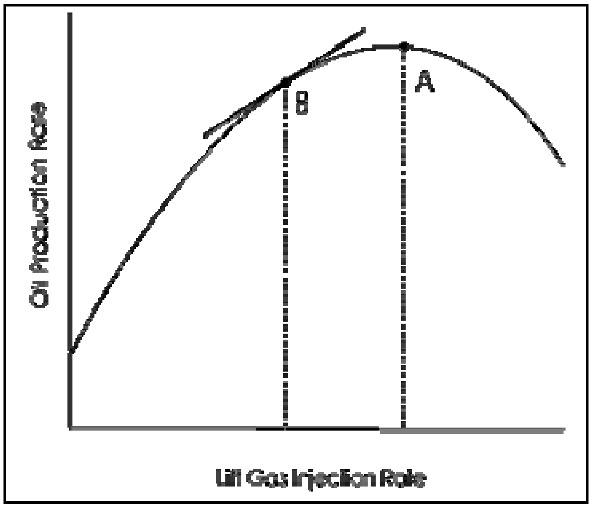


Figure 3. Economic point and optimum point in gas lift performance curve [Eclipse Technical Description v2004A]

Having influential parameters quantitatively available from a real field we optimized the injection position and gas injection rate in the individual wells using the Commercial Package software (expanded more in section 7). The obtained results were in good agreement with the real world designs already implemented in the field. This way we were assured of having our available field data as a reliable set of reference optimum criteria. We then tried adopting the best Neural Network architecture, and their output results were then compared with the outputs of the available field data and the Commercial Package outputs. This was done through the use of the data from 36 wells for the training step and testing the networks with the rest of the 4 remaining wells.

2.1 Conventional Methodology: Nodal Analysis

The system analysis approach, often called NODAL analysis, has been applied for many years to the systems composed of interacting components. Its application to well producing systems was first proposed by Gilbert in 1954 and was discussed by Nind in 1964 and Brown in 1978 [12].

NODAL analysis requires first selecting a node and calculating the node pressure, starting at the fixed or constant pressure existing in the system. These fixed pressures are usually mean reservoir pressure ($\overline{P}_R$) as the inlet pressure and either wellhead pressure (P_{wh}) or separator pressure (P_{sep}) as the outlet pressure. The node may be selected at any point in the system (Fig. 1).

Components begin with the static reservoir pressure, ending with the separator, and including inflow performance as well as flow across the completion, up the tubing string (including any down hole restrictions and safety valves), across the surface choke (if applicable), through horizontal flow lines, and into the separation facilities and are then analyzed [13]. The expressions for the flow into the node and for the flow out of the node can be expressed as:

$$\begin{aligned} P_{node} &= P_{inlet} - \Delta P\,(upstream\ components) \\ &= P_{outlet} + \Delta P\,(downstream\ components) \end{aligned} \tag{1}$$

The two criteria that must be met are: 1- Flow into the node equals flow out of the node and 2- Only one pressure can exist at the node for a given flow rate.

The performance of a gas lift well can also be treated similar to a flowing well with the only difference that the tubing string is divided into two sections with the dividing point placed at the depth of the gas injection. The section below the gas injection point contains the gas produced from the formation only, whereas the one above the injection point contains the injected gas volume as well.

3. Artificial Neural Networks

Neural-network research can be traced back to a 1943 paper by McCulloch and Pitts [14]. In 1958, Rosenblatt[15] invented the perceptron. Widrow [16] developed a similar network called Adeline. Minskey and Papert [17] pointed out that the perceptron theorem obviously applies to those problems in which the structure is capable of computing. They showed that elementary calculation cannot be solved by single-layer perceptrons.

Fig. 4 is a schematic diagram of a typical neuron that is the building block of an artificial neural network.

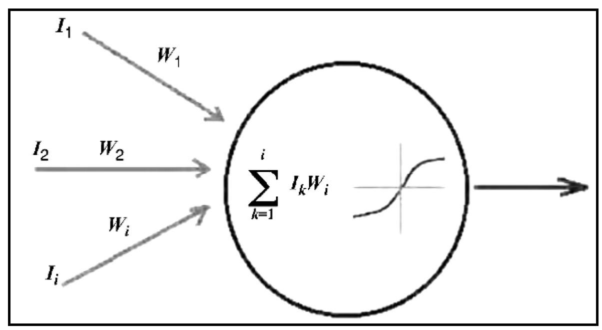


Figure 4. Artificial neuron or a processing element [18]

ANNs, like people, learn by experiment. They use input–output parameters to be trained to recognize the correct relationship. Once successfully trained, the network can be employed to compute the values of the output variable for inputs that are similar but not necessarily the same as those used in training. In petroleum engineering, the training data may be assembled from experimental data, past field data, numerical reservoir simulation, or a combination of these [19-21]. Among the various types of ANN, multilayer perceptron neural network trained with a back-propagation algorithm is perhaps the most popular network architecture in use today. A typical ANN consists of an input layer, an output layer, and a number of hidden layers.

The number of neurons in the input layer corresponds to the number of parameters that are being presented to the network as input. The neurons in the hidden layer or layers are responsible primarily for feature extraction. They provide increased dimensionality and accommodate such tasks as classification and pattern recognition.

3.1 Feed-forward, back propagation and the learning concept

Feed-forward (unidirectional) neural net, one of the most popular neural networks, provides a flexible tool to generalize linear regression because it does not require any relationships between variables [22]. Usually feed-forward neural net is arranged in multiple layers: one input layer, one output layer and one or more hidden layers. Each layer contains a number of nodes (also called neuron's processing units). The neurons in each hidden layer are represented by a weight matrix W, a bias vector β, a net input vector ε and an output vector o. Every node in any hidden layer sums its weighted inputs, adds the bias constant and then the output value of this node is calculated by applying an already chosen function (known as a basis, activation, or transform function) to the weighted sum. In this manner, input values are passed through the network topology and transformed into one or more output values. The output values are then compared to the desired values to adjust the weights and bias in the nodes.

The original transform step function or the so-called threshold function (with f(x) =1(x >0)) was proposed by McCulloch and Pitts [14]. However, through the years the artificial neuron model has-been modified to include other functions. The function *f* can be linear or nonlinear. The step, linear, sigmoid, hyperbolic-tangent functions and others can be named.

Learning is the main process in neural net operation because the simulation process depends on it. Mathematically, learning is the process by which a set of weights are found that produces the expected output when a net is presented within an input. Therefore, ANNs learn tasks by changing the weight of links between nodes. In the training process of a Back Propagation Artificial Neural Network (BP-ANN), the error between the network outputs with the desired one is propagated through the network. According to this, the weights are adjusted. This process continues until the network output reaches an acceptable value. This training process leads to the learning of ANN. When this process has finished, the ANN is ready to simulate other inputs. Back Propagation ANNs have already been used to model and simulate various processes [22].

As the real and the needed outputs are converged the learning is finished. Supervised, unsupervised and enhanced learning or other types of learning can be named [23].

4. Adopted methodology

The algorithm used is the Error Back Propagation algorithm, and the logic sigmoid function (Eq. 2) was used for activation purposes.

$$f(x) = \frac{1}{1 + \exp(x)} \tag{2}$$

In the process, the outputs were normalized to vary between zero and unity. The *O* symbol denotes the output, which can be D_{inj} or Q_{inj}. The symbol O_{old} is the old output and O_{new} represents the varied output.

$$O_{new} = \frac{O_{old} - \min(O_{old})}{\max(O_{old}) - \min(O_{old})} \tag{3}$$

4.1 The optimum network architecture

For finding the optimum network design a trial and error attempt was undertaken, starting with one hidden layer and the number of hidden units was set almost equal to the number of inputs divided by two. Hidden units were then gradually added. The maximum number of hidden units is rarely required to exceed more than 4 times the number of inputs. The architecture was retrained at least 3 times (up to 10 times is recommended) with different initial weight randomizations and only the best one was saved for comparison with other architecture.

The optimum number of nodes required in the hidden layer is problem dependent, being related to the complexity of the input and output mapping, the amount of noise in the data and the amount of training data available. If the number of nodes in the hidden layer is too few the back propagation algorithm will fail to converge to a minimum during training. Conversely, too many nodes will result in the network over fitting the training data, resulting in poor generalization performance.

As examples, the schematic diagrams of the fully connected networks we finally adopted for this study are given in Figs. 5 and 6. Different network architecture was designed for obtaining accurate models for estimation of D_{Inj} and Q_{GasInj} as functions of the other nine variables. None of the neural networks gave acceptable matches by one or three hidden layers, however the two hidden layer network gives good results for D_{Inj} and Q_{GasInj}. Subsequently, in the evaluation phase with six neurons in the first hidden layer and thirteen in the second one, D_{Inj} was estimated. Furthermore, another structure with seven neurons in the first layer and ten neurons in the second layer were used for the estimation of Q_{GasInj}. Other designs were disqualified because they were not capable of predicting data other than the training data.

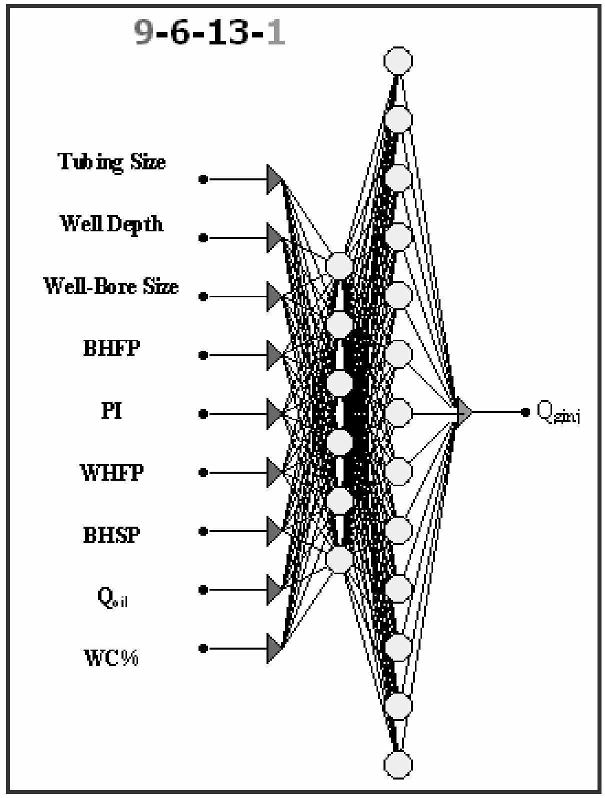


Figure 5. Structure of ANN designed for optimal gas injection rate

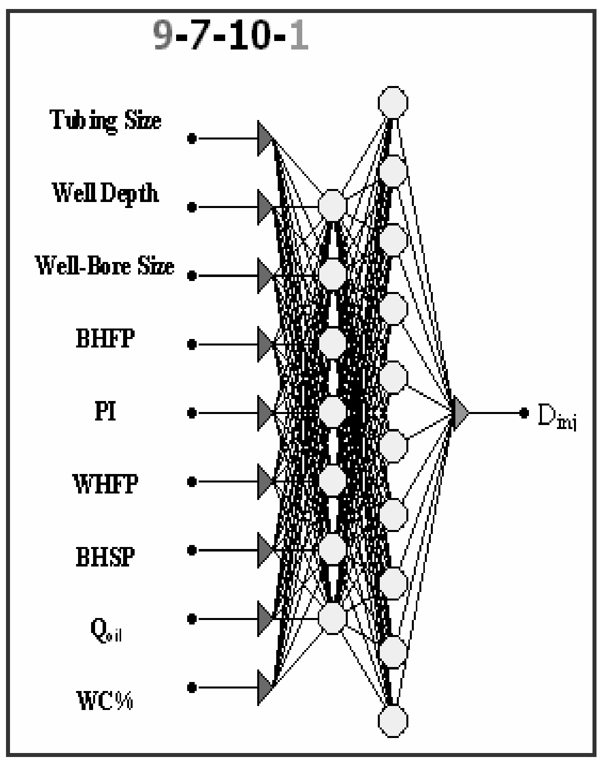


Figure 6. Structure of ANN designed for optimal injection depth

4.2 Training and evaluation phase

A number of codes were programmed in MATLAB. The network training system is offline and feeding the training data to the network was undertaken in a pattern by pattern and stochastic manner. The training data were proposed to the network in a stochastic manner for prevention of early saturation of neurons. The results are discussed next.

5. Results and Discussion

After different networks were designed for these two parameters and the best architecture was found, it was the turn for the testing stage. We used the data of 4 wells (10% of total number of wells) for the network testing.

The data used for the test phase are given in Table 2 and the results of these network tests are given in Table 3. Subsequently the gas lift system for these 4 wells was modeled using the Commercial Package software. We then optimized the system for obtaining the best injection point and find the best injection rate. The output graph is given for the Test Well No. 1 for demonstration in Fig. 7 and for all the Test Wells in Table 4.

The scatter plots for both Injecion depth and Gas Injection Rate are graphically presented in Fig. 8. The deviation of ANN results from the target values can also be assessed via the graphical presentations given in Fig 9.

Table 2. Data used for the Test phase

Well No.	Tubing Size (in)	Well Depth (ftDD)	Well bore Size	BHFP (psi)	PI	WHFP (psi)	BHSP (psi)	Q_{oil} (STB/day)	WC %	Q_{gasinj} (MMSCFD)	Depth of Injection (ft)
Test 1	5	12860	5.875	4660	2.35	565	5085	1000	0	2.9	10900
Test 2	4.5	12950	5.875	5300	2.83	437	5933	300	1.6	1.2	10988
Test 3	5	12614	5.875	4538	2.4	567	4650	1700	0.1	1.6	11569
Test 4	4.5	12378	5.875	4211	2.54	631	5560	2000	0	1.5	12276

Table 3. The neural networks results

Well No.	Real Optimum Depth of Injection (ftDD)	Real Optimum Gas injection rate (MMSCF)	Optimum Depth of Injection (ftDD) with ANN	Optimum Gas injection rate (MMSCF) with ANN
Test 1	10900	2.9	10847.54	2.9245
Test 2	10988	1.2	10995.65	1.2085
Test 3	11569	1.6	11521.35	1.560583
Test 4	12276	1.5	12305.65	1.5214

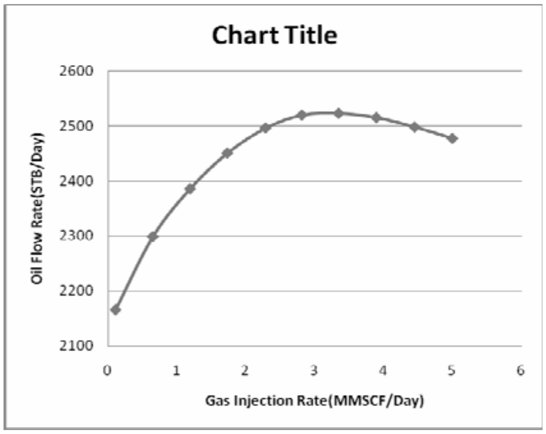
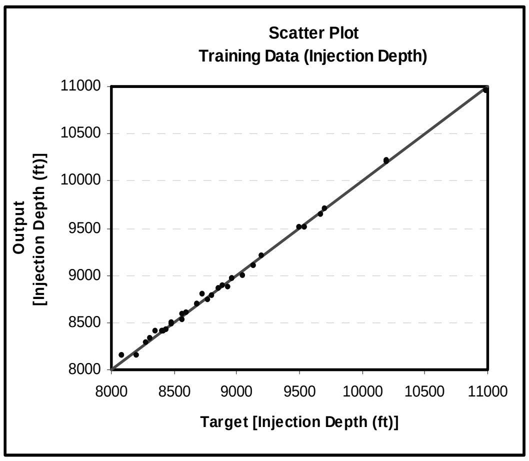


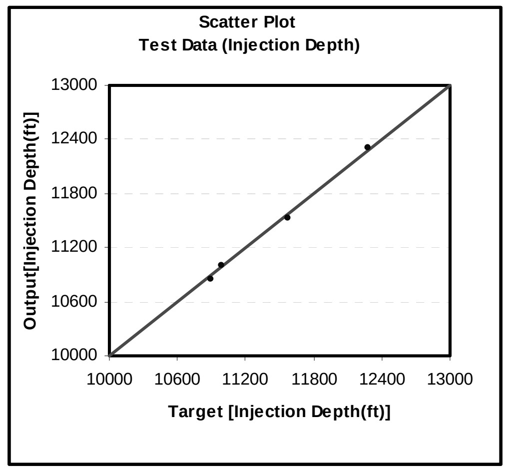
Figure 7. Finding the best injection rate for well No.Test1 using the Commercial Package software optimization output

Table 4. The Commercial Package results

Well No.	Real Optimum Depth of Injection (ftDD)	Real Optimum Gas injection rate (MMSCF)	Optimum Depth of Injection (ftDD) with Commercial Package	Optimum Gas injection rate (MMSCF) with Commercial Package
Test 1	10900	2.9	11000	3.4
Test 2	10988	1.2	12000	1.25
Test 3	11569	1.6	11200	1.5
Test 4	12276	1.5	11500	1.75



(a)



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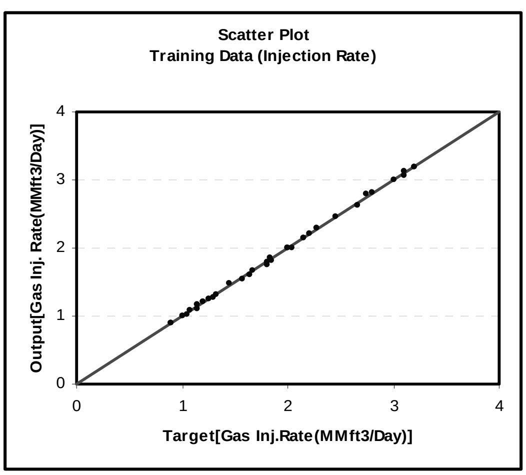

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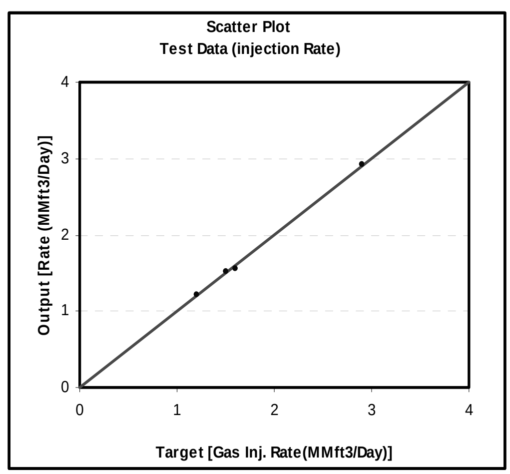

(d)

Figure 8. Resulting Scatter Plots: (a) Training Injection Depth Data, (b) Testing Injection Depth Data, (c) Training Injection Rate Data, (d) Testing Injection Rate Data

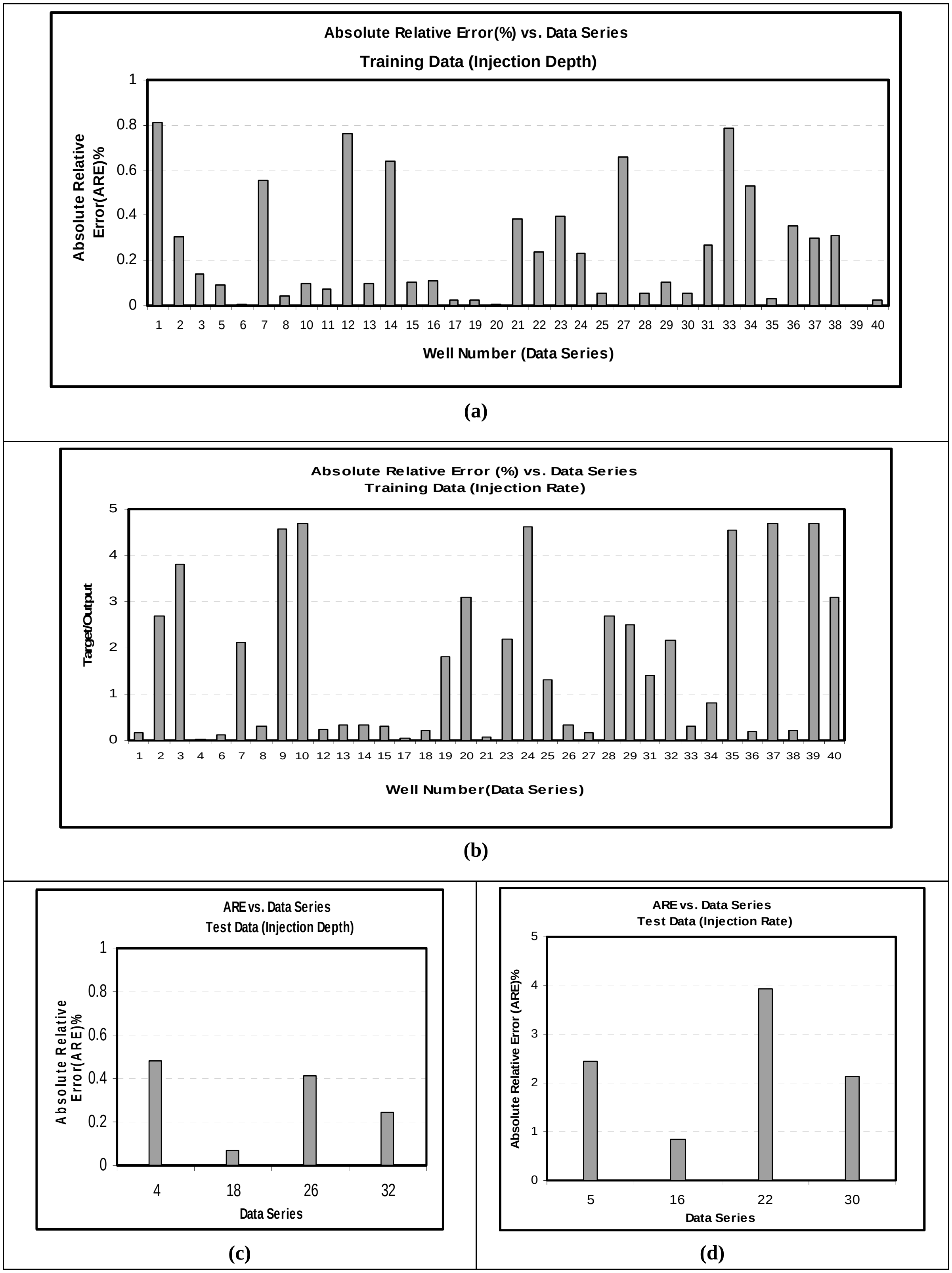

Figure 9. Absolute relative percentage error for (a) Injection depth training data, (b) Injection rate training data, (c) Injection depth testing data, (d) Injection rate testing data

Comparisons between Tables 3 and 4 are given in Tables 5 and 6.

Table 5. The Optimum Gas injection rate results of Commercial Package and neural network

	ANN	Commercial Package
Minimum absolute percentage relative error (%)	-0.85	0.04166
Average absolute percentage relative error (%)	2.34543	11.08117
Maximum absolute percentage relative error (%)	3.94175	17.24

Table 6. The Optimum injection depth results of Commercial Package and neural network.

	ANN	Commercial Package
Minimum absolute percentage relative error (%)	0.069621	3.18955
Average absolute percentage relative error (%)	0.301077	4.90957
Maximum absolute percentage relative error (%)	0.481284	9.21004

6. Conclusion

Two neural-network-based models were presented for the prediction of gas injection rate and the injection depth for artificially gas lifted oil producing wells given specified well data. A mean absolute error of 0.037% for the gas injection rate and 0.63% for the injection depth were obtained. The best network architecture was constructed in terms of the number of neurons and the number of network layers. An artificial neural network model for gas lift optimization was developed based on data points recorded in 40 wells that are under gas lift system. The approach presented in this study automates the process. Furthermore, this approach provides a new way to speed up the calculations and to bypass the use of the tedious and time-consuming software training; it may also reduce the cost of the software supply.

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