JEAS

JOURNAL OF ENGINEERING AND APPLIED SCIENCES

Journal of Engineering and Applied Sciences, Volume 21, Number 1, Dec. 2022, 842 - 858

Production optimization using gas lift incorporated with artificial neural network

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Abstract

This work investigates the impact of artificial neural networks on gas lift optimization to improve the Crude oil production. Data were collected from two wells which was trained in neural network using MATLAB 7.9 neural network toolbox. The data was divided into three parts; training (60%), validation (20%) and testing (20%), and was done on 20 hidden neuron multi-layer feed-forward neural network. The result indicated that the data from the two wells were well trained for accurate optimal prediction as the R-value was close to 1 and the Mean Square Error (MSE) was very low. The average error comparing the actual and predicted data was minimal using few data from the general data. The behavior for both wells follow same pattern and can be concluded that for optimal production to be achieved, it will involve a reduced Well head parameter and Gas Compressor Suction pressure and a higher Gas compressor Injection pressure. It can be concluded that artificial intelligence have a very high impact on the optimal Crude oil production using gas lift.

Keywords: Gas lift, neural network, MATLAB, Optimization

1. Introduction

As a reservoir produces, it naturally experiences pressure drop and water cut increases, which can cut or reduces its production flow rate. When this is encountered, artificial lift methods, including gas lift can resume or increase the production rate by supplying additional energy to the fluid in the well (Mohammad, 2012). The major reason for installing a gas lift is to increase the drawdown on the production formation by inputting gas into the lower part of the oil column and consequently reducing the flowing gradient in the oil column. In the petroleum industry, Gas lift optimization is now been thoroughly discussed as a proper Gas lift optimization can reduce the operation cost, increase the net present value and maximize the recovery from the asset (Mohamad et al., 2016). A definition which can be accepted for a Gas lift optimization is to obtain a maximum output under specific operating conditions. Gas lift optimization is a continuous process and can be viewed from two levels of production optimization; optimizing the surface facilities which can be seen as total field optimization and optimizing the injection rate that can be achieved by standard tools software.

In achieving an optimization process for gas lift, so many researchers have suggested so many tools which have not been too efficient, though can also improve the performance of the well. Most of the works tried to approach gas lift optimization using regressive method and other optimization tools like linear programming, Leg radian method, Interpolations, etc (Ntherful, 2013; Benjamin, 2012; Dinesh et al, 2016). Most methods explored have not produced good intelligent system to understand itself automatically, for optimal production. Such system if actualized can reduce cost thoroughly and human labour.

Artificial intelligence which is the major discussion in the world today can also be seen in Gas lift optimization. Though discussions have been raised on the possibilities of using Artificial intelligence for Gas lift optimization but only few works have applied it. Chukwuka et al. (2014) tried to study the oil well characterization using neural network and genetic algorithm. The work was limited to cost optimization without considering most of the well properties like Gas compression Injection pressure, Well head choke size, Gas compression suction pressure, etc. Other articles which applied Machine learning could not give a good results or analysis on the Neural network application to justify their analysis. This work hopes to establish these gaps in reconciling the neural analytic application and its effect on the gas lift optimization. For optimal production rate, this work employed neural network application to Gas lift optimization using the well properties data collected from Waltersmith Petroman oil limited. The data will be analyzed using MATLAB 7.9 Neural Network Toolbox and its result will be compared with normal operation to ascertain the state of the production rate after Artificial neural Network is applied.

Continuous gas lift is a process of producing mature and depleted reservoir which can no longer produce using their natural energy (Garrouch et al., 2020). Their operation consists of injecting gas through the well annulus into the producing fluid column, reducing the hydrostatic pressure. When gas is present inside the producing tubing at the deepest point, it aids the flow pressure of the bottom hole to allow fluid to flow from the reservoir to surface (Mohamad et al., 2016). Many works have suggested methods of gas optimization to maximize production rate and reduce cost of production. Dinesh et al. (2016) considered real-time optimization under uncertainty applied to gas lift well network. The work considered daily production optimization in the upstream oil and gas domain. In order to maximize revenue, the author(s) tried to find the optimal decision variables that utilizes the production system efficiently. The production model is subject to uncertainty that have been overlooked and the optimal solution is based on nominal models which can render the solution useless and may lead to infeasibility when implemented. The author(s) proposed using scenario-based optimization to reduce the conservativeness of the proposed model. The work demands more measurement to know the time state of the well.

Chrisman et al. (2017) considered optimization of oil production using gas lift Macaroni in X field. The author(s) considered an X field where many gas wells have stopped flowing years ago and cannot be considered economically anymore. Gas field was considered as the best solution which is proper to sandy soil characteristics. The objective was to maximize the production rate, which is done by installing the new tubing called the macaroni tubing inside the existing tubing of which the gas lift valve was installed inside the macaroni tubing. Results were collected on the production rate after the installation which shows that the new design could generate oil production rate of 425STB/day. The process was able to save cost and optimize the production rate. Shedid and Mostafa (2016) considered a simulation study of technical and feasible gas lift performance using PROSPER software. The aim was to critically analyze each well in order to maximize the production earnings. The PROSPER simulator was used to model all wells individually using actual PVT data of the deviation survey, down-hole completion, geothermal gradient and average heat capacities. The result indicated that gas lift optimization process is inevitable for obtaining high production rates considering several variables like injected gas compositions, water cut and well head pressure which have an important effect on gas lift, while gas roughness has minimal effect on increasing oil production. The work was simulated on actual data.

Okorocha et al. (2020) reviewed the production challenges and gas optimization strategies in Gas lift optimization for oil and gas production process. Drawbacks or challenges encountered in gas-lift optimization according to the author(s) are deterioration of oil well, incorrect production metering, instability of gas compressor and over injection of gas. To reduce operational cost, the author suggested that artificial intelligence or machine learning could be introduced into gas lift to reduce operational cost, which in turn will maximize the production rate and increase profit. Garrouch et al. (2020) further discussed that the flowrate of a single vertical well undergoing Gas lift operation is affected by the fluid flow potential gradient along the well, a porous and permeable reservoir interfaced contributing with a fluid feed and the wellbore geometry which may consist of concentric pipes of varying diameter and lengths rather than single diameter pipes. The author(s) considered a pragmatic approach for optimizing gas lift, applying a dimensional analysis to the highly non-linear production problem in order to develop an empirical model for predicting the optimal gas injection rate and the optimal production rate that may be produced from continuous gas lift operation. The proposed method evades the assumption process associated with non-linear regression analysis in predictions associated with gas lift optimization.

Kashif et al. (2012) tried to provide an insight on techniques and methods developed for gas lift continuous optimization process. According to the author(s), it ranges from isolated Well analysis to real time multivariate optimization schemes encompassing all wells in the field. Some methods are limited to their neglects of treating the effect of inter-dependent well and common flow line while other methods are limited due to large scale networks of wells which are difficult to produce. The methods employed from simple variable minimization to more sophisticated mixed-integer non-linear (MINLP) optimization scheme. Depending on the formulation adopted, some optimization scheme could be preferred than others. Derivative free scheme like Genetic Algorithm (GA) and Polytope can be applied in most settings but suffers from a high computational overhead if the function is costly to evaluate. The method could be improved using a numerical approach.

Chukwuka et al. (2014) considered possibility of Gas lift optimization using neural network combined with genetic algorithm for cost reduction in gas-lift. The method according to the author will reduce the over-allocation of gas to the oil wells. Though the work addressed the oil production of wells using non-performing wells thorough work was not done on the neural network approach rather the result indicated more work on the genetic algorithm. The result shows an improvement on the well performance and profit actualized. Out of all the reviewed researches only one considered Neural Network application with Genetic Algorithm though considering the cost optimization majorly. Production rate was not dealt with holistically. Also, most researches considered traditional methods like linear programming, Genetic Algorithm etc but much work have not been done on using Artificial Neural Network to optimize the well production rate. The Objective of this research is to cover this gap by using Artificial Neural Network to optimize the Well Production Rate and create an automated operation which in turn hopes to minimize cost of production.

2.0 Research method

2.1 Data collection

This study was carried out on Ibigwe well 1 and Ibigwe well 2 of Waltersmith Petroman oil limited. The study was for a period of 2years. These data are daily process data that are always observed and recorded by the production personnel on board. These include the well head parameters, compressor parameters, volume of gas injected and well production rates etc.

2.2 Neural network analysis

To optimize the performance of the Gas lift production rate, Neural Network was used to for accurate prediction and computing. The data was divided into inputs and targets and was analyzed using MATLAB 7.9 Neural Network Toolbox. The input variables are the well head parameter, well head choke size, compressor injection pressure and the gas compressor suction pressure while the target value is the well production rate. The aim of the analysis is to get an accurate, optimal prediction of the behavior of the well to improve the automatic gas lift properties prediction in order to optimize the production rate of the wells.

A typical neural network has neurons often called units or nodes, which could be from complex of dozens to even millions and are arranged in layers. All units can be classified into input units, hidden units and output units which connect the layers on either side. Rectifier Linear Unit (ReLU) activation was considered which takes a real-valued input and replaces the negative values with zero. It is trending in the field of engineering because it is relatively simple and efficient function which avoids and rectifies the gradient vanishing problem.

$$R(x) = \max(0, x) \tag{1}$$

The neural network considered have 3 inputs, 1 target and 20 hidden neurons as shown in Figure 1 below. Having data containing features and results, the multi-layer perception will learn the relationship between features and results in the given data set and predicts the results from the new data set. Generally, n inputs are sent and weight are generally assigned to the units at first place.

$$x = x_{wthp}, x_{gcip}, x_{whsc}, x_{gcsp} \ \mid x \in R^n \tag{2}$$

$$w = w_{wthp}, w_{gcip}, w_{whsc}, w_{gcsp} \tag{3}$$

For the training session, the weight will be adjusted for more accurate approximation

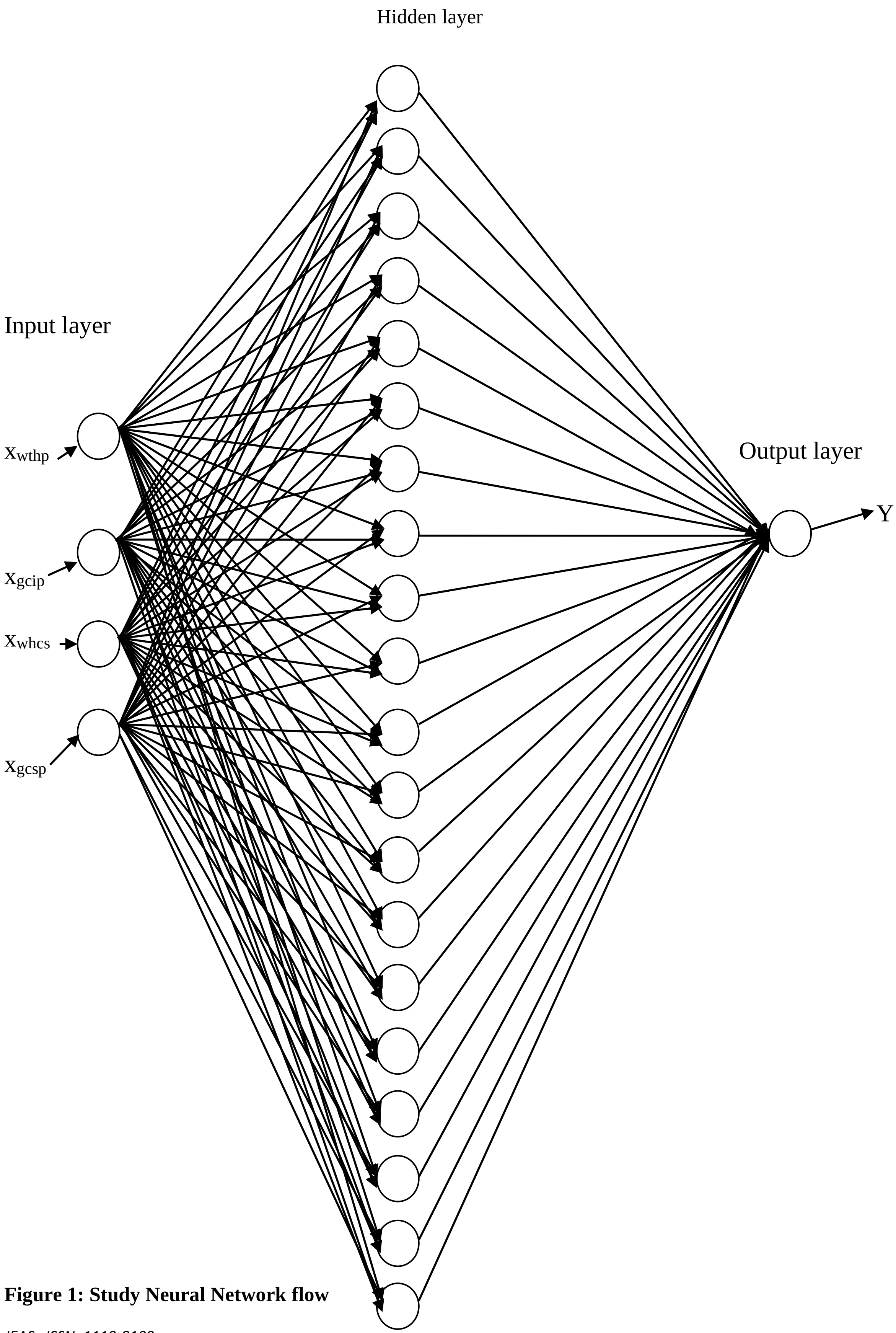

Figure 1: Study Neural Network flow

For the hidden layer, a pre-state P is initiated by taking dot product of x and w ;

$$P = x_{wthp}w_{wthp} + x_{gcip}w_{gcip} + x_{whcs}w_{whcs} + x_{gcsp}w_{gcsp} + b \tag{4}$$

The total matrix to be created at the output using four inputs, twenty hidden neuron and one output is 4x20 matrix. Each matrix is called w_{ki}, where i is the neuron position and k is the input position. This shows that we have twenty pre-states, each stores the dot product of corresponding inputs and weights. The pre-state goes through an activation function, α, called the state (S) inside the hidden neuron,

$$S = \alpha(W_i X_i + b_i) \tag{5}$$

Neural network learns from pattern of data and tries to make accurate predictions of them. The optimization problem is to set the neural net V that minimizes the error function, which can be seen as,

$$E = \frac{1}{N}\sum_{i=1}^{q}\left\|t^i - y^i\right\| \tag{6}$$

Where V can be built ideally as,

$$V(x^i) = t^i \tag{7}$$

Where t^i is the target value, x^i is the input values and N is the number of training patterns. The error of the neural net given a target t will be,

$$E(w_1, w_2, b_1, b_2) = \frac{1}{2}(t-y)^2 = \frac{1}{2}\left[t - \left(w_2\delta(w_1x + b_1)\right) + b_2\right]^2 \tag{8}$$

Our aim is to minimize the error, which will cause us to move to the opposite side of the gradient. To achieve a better error, it will be good to update weights/biases in the training session. Using gradient descent, the weights/biases (u) can be updated with the equation,

$$u_{new} = u_{old} - \beta\frac{\partial E}{\partial u} = u_{old} + \beta\Delta u \tag{9}$$

Where β is called the learning rate and the change in u is computed by the chain rule of the error. The negative sign is incorporated into Δu because the derivative of the (t-y) will always be negative t-y.

3.3 Splitting of the data for neural analysis

Data is divided into 3 during the Analysis training session for proper prediction. The data is divided into the following;

- Training data set: this is the sample of data used to train the Neural network. For the purpose of this work, 60% of data was used for training purpose.
- Validation data set: this is the sample of data used to provide an unbiased evaluation of the final version of the neural network on the training data set while tuning the hyperparameter. 20% of the data set was used for this purpose.
- Testing data set: this is the sample of data used to provide an unbiased evaluation of the final version of the neural network fit on the training data set. 20% of the data set was used for this purpose.

4.0 Results

From the analysis done, the neural network results were gotten and compared with the optimal production rate without neural network. The two well data were trained in MATLAB 7.9 Neural Network Toolbox and the results for the regression fitting and average errors were plotted.

Table 1: Neural Network Regression results

	MSE	R-value
	WELL 1	
Training	0.31218	0.98288
Validation	0.55661	0.96816
Testing	0.38499	0.97752
	WELL 2	
Training	0.22266	0.98596
Validation	0.68595	0.96232
Testing	1.38166	0.93587

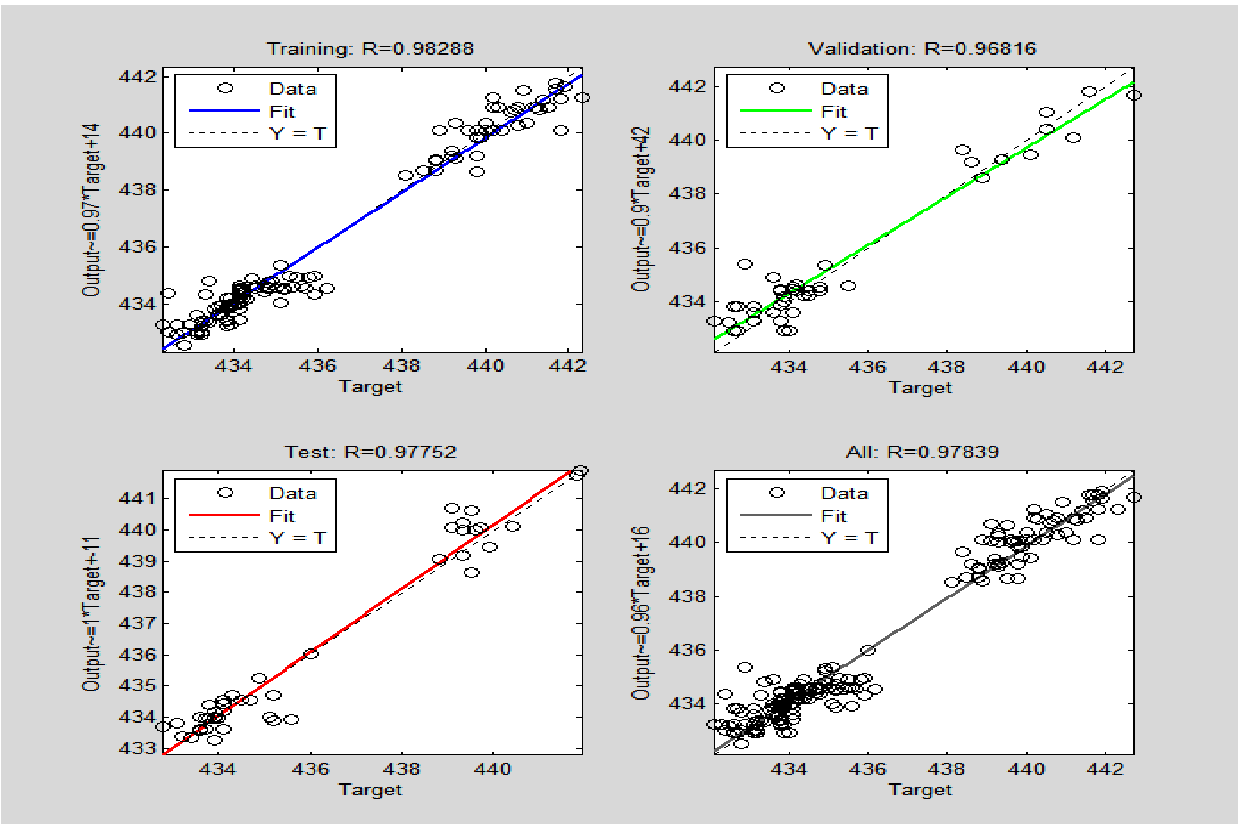

Figure 2: Regression results for 20 hidden Neuron for Well 1

The regression result for well 1 shows a very good results as the R values for the training (R=0.98288), validation (R=0.96816) and test (R=0.97752) and close to 1 according to Figure 2 and Table 1. The output tracks the targets very well for training, testing and validation and the average R-value is 0.97839. This shows that the network is properly trained, validated and tested for proper predictions using the input and the target values.

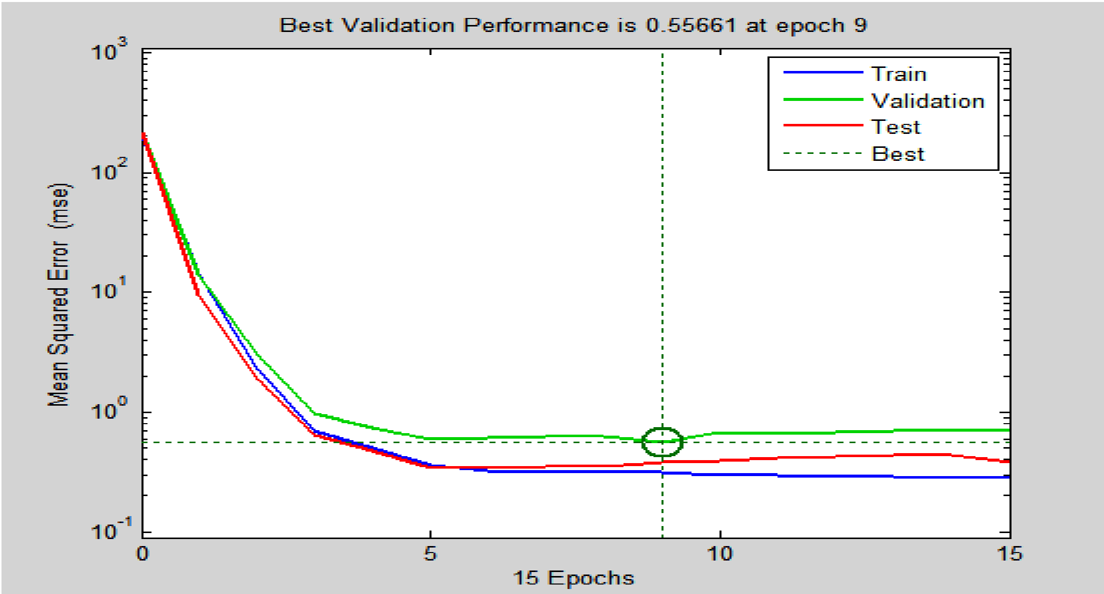

Figure 3: MSE results for 20 hidden neurons for well 1

Considering the mean square error in Figure 3, the minimum validation error is at 0.55661 at 9th (epoch 9) iteration. The result can be considered perfect since the test result and the validation result is following almost same pattern and the errors are also relatively small for training (0.31218) and testing (0.38499).

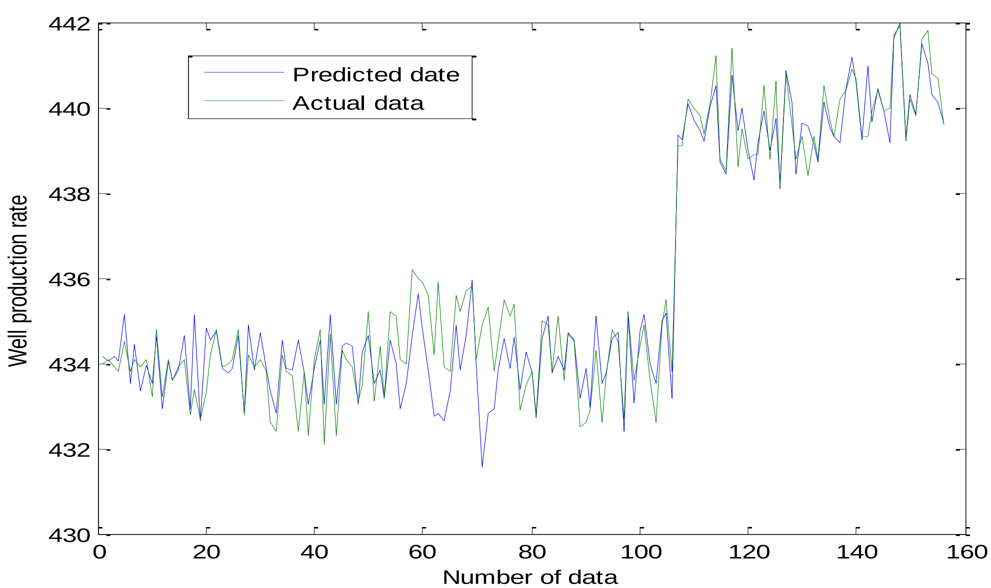

Figure 4: Comparison of well production rate for actual and predicted value for Well 1

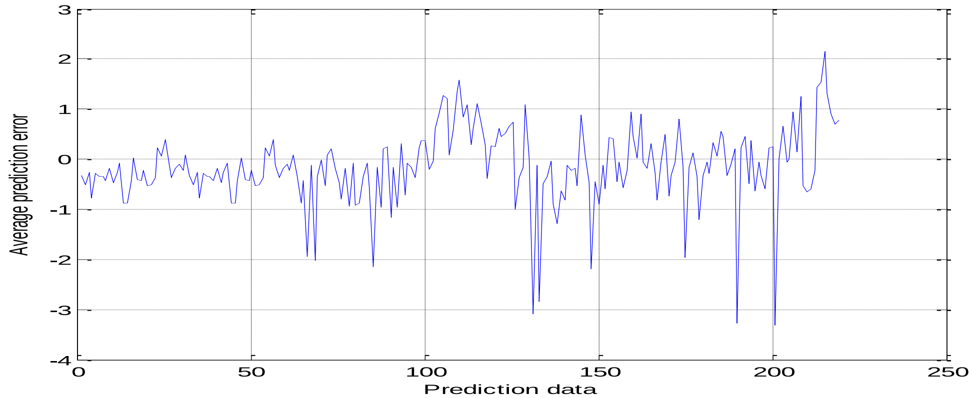

Figure 5: Average Prediction error for Well 1

From Figures 4 and 5 it can be seen that the average prediction error is minimal comparing the predicted value with the actual value. This shows that the predicted value can actually be trusted for proper optimization.

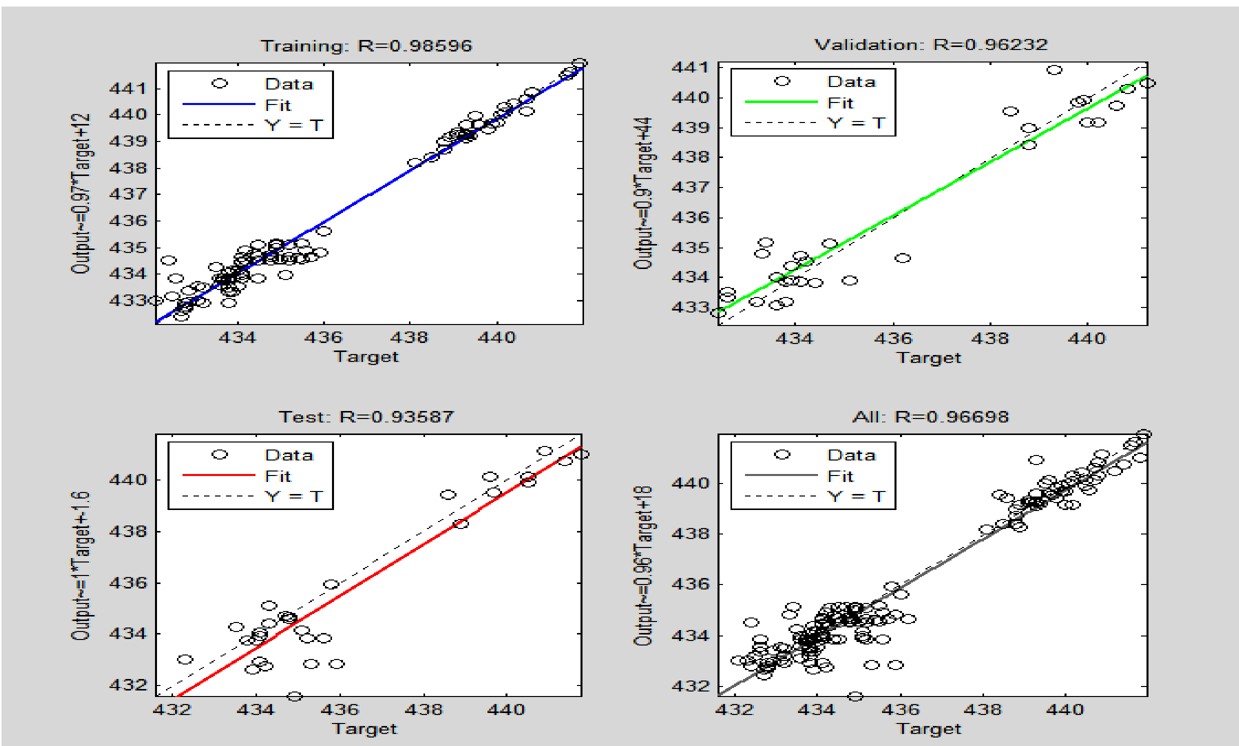

Figure 6: Regression results for 20 hidden neurons for well 2

The regression result for well 2 shows a very good results as the R values for the training (R=0.98596), validation (R=0.96232) and test (R=0.93587) and close to 1 according to Figure 6 and Table 1. The output tracks the targets very well for training, testing, and validation and the average R-value is 0.96698. This shows that the network is properly trained, validated and tested for proper predictions using the input and the target values.

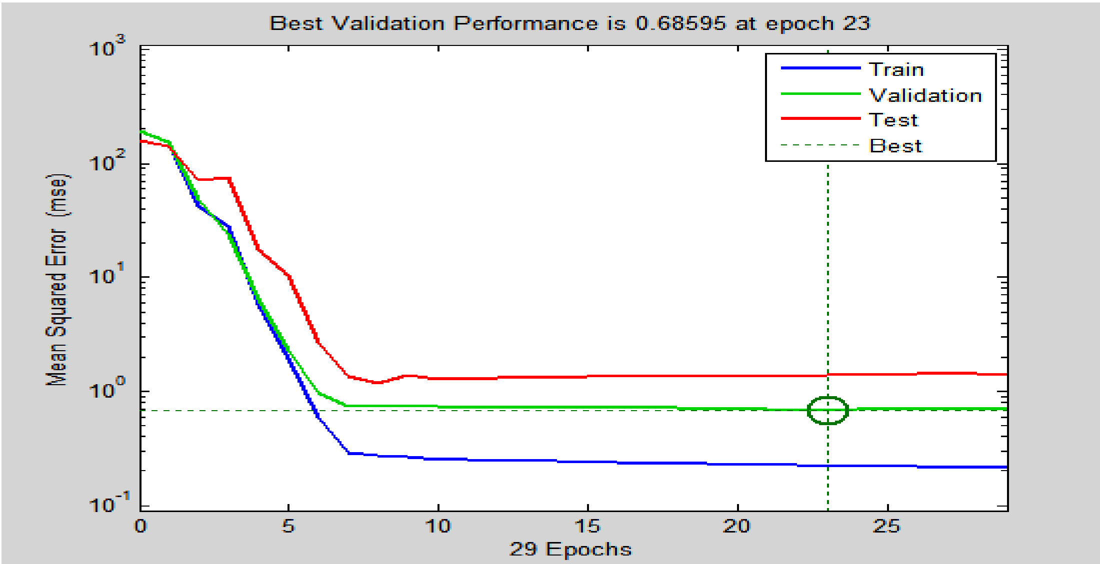

Figure 7: MSE results for 20 hidden neurons for well 2

Considering the mean square error in Figure 7, the minimum validation error is at 0.68595 at 23rd (epoch 23) iteration. The result can be considered perfect since the test result and the validation result is following almost same pattern and the errors are also relatively small for training (0.22266) and testing (1.38166).

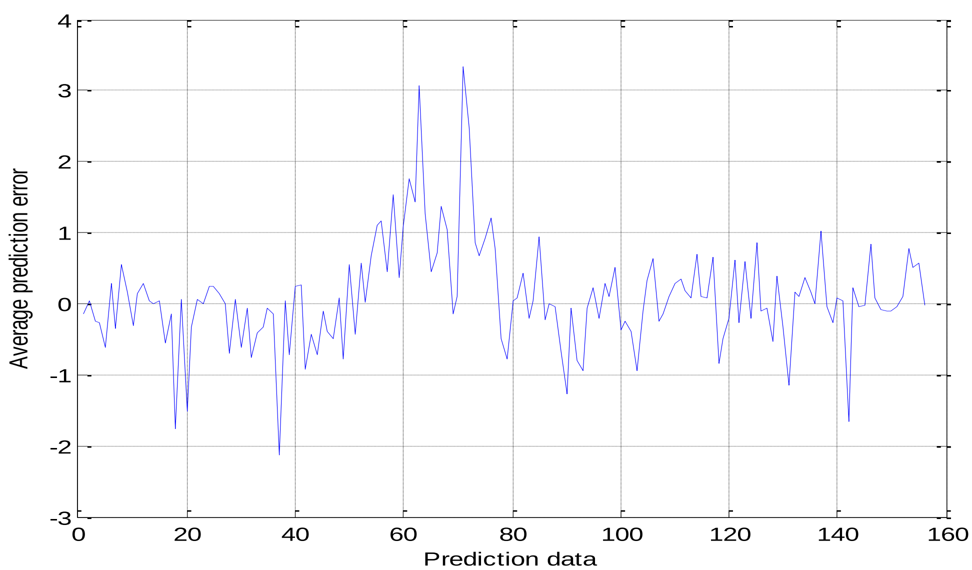

Figure 8: Data prediction error

From Figure 8, it can be seen that the average prediction error is minimal comparing the predicted value with the actual value. This shows that the predicted value can actually be trusted for proper optimization.

Table 2: Optimal production rate data

WELL 1	
WPR (Without NN)	458.7BBL
WPR (With NN)	479.4BBL
WTHP (Without NN)	115Psi
WTHP (With NN)	114Psi
GCIP (Without NN)	1254Psi
GCIP (With NN)	1257Psi
GCSP (Without NN)	35Psi
GCSP (With NN)	32Psi
WELL 2	
WPR (Without NN)	855.5BBL
WPR (With NN)	881.9BBL
WTHP (Without NN)	85Psi
WTHP (With NN)	79Psi
GCIP (Without NN)	1336Psi
GCIP (With NN)	1349Psi
GCSP (Without NN)	34Psi
GCSP (With NN)	34Psi

From the optimal production result in Table 2, there was an improved well production rate for both Well 1 and 2 using the from 458.7BBL to 479.4BBL for well 1 and 855.5BBL to 881.9BBL for well 2. The values followed same trend for well 1 and well 2 except the Gas Compressor suction pressure which is constant (34Psi) at optimum for well 2 and reduced from 35Psi to 32Psi for well 1 using neural networks. The gas compressor injection pressure increased for both wells increased from 1254Psi to 1257Psi using neural network while from 1336Psi to 1349Psi for well 2 using neural network.

Generally, from the results gotten it can be observed that higher production rate can be achieved when there is reduced well head parameter and gas compressor suction pressure and a higher gas compressor injection pressure. Comparing the results gotten with other research done (though much work, considering thorough analysis on optimizing the production rate have not been done) applying neural network will proffer better solution than other traditional methods like linear programming and genetic algorithm considering optimization of well production rate.

4.1 Research findings, Applications, Recommendations and Contribution to Knowledge

At the conclusion of the research the following Findings, Applications and Recommendations as well as contribution to knowledge can be proffered based on findings,

- Gas lift systems incorporated with Artificial Intelligence will go a long way to minimize the cost of production and optimize the well production rate.
- For optimal well production, it will be more advisable to incorporate Neural Network in the design of gas lift systems than other AI systems.
- Neural network will optimize the production rate while maintaining appropriate well behaviours.
- Neural network application will guarantee automated operation thereby reducing manpower operation while still guaranteeing optimal production of the well.

- Other AI tools like Fuzzy logic should be incorporated with Neural Network in Gas lift Optimization.
- The work gave deep knowledge on the application of Neural Network and also gave factors that can affect the Gas-lift of Crude Oil Wells.

5.0 Conclusion

This study investigated the impact of neural network on the performance of gas lift. It considered the parameters which affects the production rate of a well. For the study, two wells were considered and it was observed that neural network have a great impact on the gas lift optimal prediction as it aid to improve the oil production rate for the two wells. This can be deduced from the minimal Mean Square Error (MSE) and the R-values for the training, validation and testing which is close to 1 showing a very good fit. For both wells, same trends were observed for the properties considered except for Gas compressor suction pressure which remained constant for well 2. Generally, it can be concluded that for optimal production to be achieved, there should be a reduced well head parameters and gas compressor suction pressure and a higher gas compressor injection pressure. This can be concluded from the trend observed from both the predicted and the observed data.

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Appendix A: Data used for the research

Table A1: Data for Well 1

Well THP (Psi)	Well Production Rate (BBL)	Gas Compressor Injection Pressure (PSI)	Well Head Choke Size (Inches)	Gas Compressor Suction Pressure (Psi)
120	433.7	1295	24/64	35
120	433.8	1294	24/64	34
119	433.1	1296	24/64	34
121	434.2	1293	24/64	34
121	433.9	1296	24/64	35
120	433.4	1296	24/64	35
121	434.1	1295	24/64	35
120	433.6	1295	24/64	35
119	433.1	1293	24/64	35
121	434.2	1294	24/64	35
119	433.3	1294	24/64	34
119	433.2	1293	24/64	35
121	434.1	1293	24/64	34
121	433.8	1294	24/64	35
119	433.1	1295	24/64	34
121	434.7	1294	24/64	35
120	433.9	1294	24/64	34
120	434	1293	24/64	35
120	434.1	1295	24/64	34
120	433.9	1293	24/64	35
120	433.8	1295	24/64	34
121	434.5	1293	24/64	35
119	433.8	1294	24/64	34
120	434.1	1295	24/64	35
119	433.9	1293	24/64	34
120	434.1	1293	24/64	34
119	433.2	1294	24/64	34
121	434.8	1293	24/64	34
119	433.2	1294	24/64	35
120	434.1	1295	24/64	34
119	433.6	1295	24/64	34
120	433.7	1295	24/64	35
120	433.8	1294	24/64	34
119	433.1	1296	24/64	34
121	434.2	1293	24/64	34
121	433.9	1296	24/64	35
120	433.4	1296	24/64	35
121	434.1	1295	24/64	35
120	433.6	1295	24/64	35
119	433.1	1293	24/64	35
121	434.2	1294	24/64	35
119	433.3	1294	24/64	34
119	433.2	1293	24/64	35
121	434.1	1293	24/64	34
121	433.8	1294	24/64	35
119	433.1	1295	24/64	34
121	434.7	1294	24/64	35

120	433.9	1294	24/64	34
120	434	1293	24/64	35
120	434.1	1295	24/64	34
120	433.9	1293	24/64	35
120	433.8	1295	24/64	34
121	434.5	1293	24/64	35
119	433.8	1294	24/64	34
120	434.1	1295	24/64	35
119	433.9	1293	24/64	34
120	434.1	1293	24/64	34
119	433.2	1294	24/64	34
121	434.8	1293	24/64	34
119	433.2	1294	24/64	35
120	434.1	1295	24/64	34
119	433.6	1295	24/64	34
120	433.9	1290	24/64	35
121	434.1	1293	24/64	34
119	432.8	1289	24/64	34
122	433.4	1292	24/64	34
119	432.7	1291	24/64	35
120	433.3	1289	24/64	33
121	434.2	1290	24/64	34
122	434.8	1290	24/64	35
120	433.9	1291	24/64	35
120	434	1290	24/64	34
120	434.1	1289	24/64	35
121	434.8	1293	24/64	34
119	432.8	1293	24/64	35
121	434.2	1292	24/64	35
120	433.9	1292	24/64	34
121	434.1	1291	24/64	35
120	433.8	1289	24/64	35
119	432.6	1293	24/64	34
119	432.4	1293	24/64	35
121	434.2	1290	24/64	34
120	433.8	1289	24/64	35
120	433.7	1290	24/64	35
121	432.4	1290	24/64	34
120	433.8	1291	24/64	34

Table A2: Data for Well 2

Well THP (Psi)	Well Production Rate (BBL)	Gas Compressor Injection Pressure (PSI)	Well Head Choke Size (Inches)	Gas Compressor Suction Pressure (Psi)
120	433.7	1295	24/64	35
120	433.8	1294	24/64	34
119	433.1	1296	24/64	34
121	434.2	1293	24/64	34
121	433.9	1296	24/64	35
120	433.4	1296	24/64	35
121	434.1	1295	24/64	35
120	433.6	1295	24/64	35
119	433.1	1293	24/64	35
121	434.2	1294	24/64	35
119	433.3	1294	24/64	34
119	433.2	1293	24/64	35
121	434.1	1293	24/64	34
121	433.8	1294	24/64	35
119	433.1	1295	24/64	34
121	434.7	1294	24/64	35
120	433.9	1294	24/64	34
120	434	1293	24/64	35
120	434.1	1295	24/64	34
120	433.9	1293	24/64	35
120	433.8	1295	24/64	34
121	434.5	1293	24/64	35
119	433.8	1294	24/64	34
120	434.1	1295	24/64	35
120	434.1	1293	24/64	34
119	433.2	1294	24/64	34
121	434.8	1293	24/64	34
119	433.2	1294	24/64	35
120	434.1	1295	24/64	34
119	433.6	1295	24/64	34
120	434.7	1293	24/64	34
119	433.8	1292	24/64	34
120	434.3	1290	24/64	33
119	433.7	1293	24/64	35
120	434.9	1288	24/64	34
120	435	1289	24/64	34
120	434.8	1292	24/64	33
119	433.2	1290	24/64	35
119	433.4	1291	24/64	35

120	434.1	1288	24/64	33
121	435.8	1289	24/64	35
120	433.8	1290	24/64	34
121	434.5	1292	24/64	33
119	433.3	1291	24/64	34
120	434.2	1289	24/64	35
120	434.1	1288	24/64	34
121	435.6	1291	24/64	35
119	433.2	1290	24/64	33
120	434.1	1292	24/64	34
121	434.9	1289	24/64	35
119	433.1	1288	24/64	33
120	434.2	1290	24/64	34
119	433.2	1288	24/64	35
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120	434.1	1289	24/64	33
121	435.2	1290	24/64	34
119	434	1288	24/64	35
119	433.9	1289	24/64	34
120	433.9	1290	24/64	35
121	434.1	1293	24/64	34
119	432.8	1289	24/64	34
122	433.4	1292	24/64	34
119	432.7	1291	24/64	35
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122	434.8	1290	24/64	35
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120	434.1	1289	24/64	35
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120	433.9	1292	24/64	34
121	434.1	1291	24/64	35
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119	432.4	1293	24/64	35
121	434.2	1290	24/64	34
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120	433.7	1290	24/64	35
121	432.4	1290	24/64	34
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121	434.8	1290	24/64	34
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121	434.1	1289	24/64	35
121	433.9	1292	24/64	33
119	433.1	1291	24/64	34
120	433.5	1290	24/64	33
121	435.2	1293	24/64	34
119	433.1	1289	24/64	33
120	434.4	1289	24/64	34
119	433.2	1292	24/64	34
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120	435.1	1292	24/64	35
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119	434	1289	24/64	33
121	436.2	1293	24/64	34
120	436	1293	24/64	36
120	435.9	1289	24/64	33