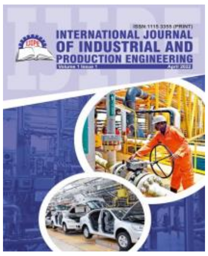

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Gas Lift Optimization of an Oil Well using Artificial Neural Networks (ANN)

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ABSTRACT

This research investigates the gas lift optimization of an oil well using Artificial Neural Networks (ANN). Through statistical analyses of two wells spanning over a two-year period, the critical correlations among wellhead pressure, production rates, and gas compression parameters were reported. Notably, a positive correlation between wellhead pressure and production rate was identified, emphasizing the pivotal role of monitoring and optimizing these operational variables for enhanced efficiency. The research integrates machine learning techniques for gas lift with model recognition and parameter estimation. Leveraging the power of algorithms, like the Levenberg-Marquardt algorithm for the model, the best performance of 0.000000584 was found after 1000 epochs (iterations). The study demonstrates the potential for real-time decision support in oil well operations, offering a pathway for improved responsiveness and adaptability to changing conditions. Practical recommendations derived from the study provide actionable insights for industry practices, facilitating advancements in oil and gas engineering. The validation of machine learning models underscores their reliability in enhancing efficiency and productivity in real-world oil and gas applications. As a culmination of these findings, the research not only advances our understanding of gas lift systems but also provides a roadmap for the implementation of cutting-edge technologies and methodologies in the oil and gas sector.

Keywords: Machine Learning; Wellhead pressure; Levenberg-Marquardt algorithm; Confusion matrix; Oil well operations.

1. Introduction

There are a lot of unknowns and risks involved in getting oil and gas from a subsurface hydrocarbon reservoir to the surface production or processing facilities. This implies that the profiles of oil and gas production around the world vary greatly from one another. At some point in the life of a field, the production rate eventually declines to a point where it can no longer produce profitable amounts of hydrocarbon. In an ideal world, every operator would like to keep oil production at this peak or plateau state for as long as possible. Most fields have a flat top, and the length of the flat top depends on reservoir productivity, but in some fields the production build-up rate begins in the first few years. Furthermore, in some scenarios, some wells drilled and completed do not flow naturally or optimally as required and as such require some forms of artificial or assisted lift system to optimize the well's production rate or revive or restore dead wells. Basically, there are two methods of artificial lift systems deployed in the oil and gas industry globally to optimize oil well's production flow rate. These are: the gas lift system, which comprises the continuous and intermittent gas lift injection where the lift gas is injected via the lift valves or orifice, the pumping system comprising the sucker-rod pump, electrical submersible pump which is an efficient and reliable artificial-lift method for lifting moderate to high volumes of fluids from wellbores (these volumes range from a low of 150 B/D to as much as 150,000 B/D), progressive cavity pump which is efficient for lifting heavy crude, hydraulic submersible pump, etc.

There are different key factors that are considered prior to artificial lift installation in the field which include analysis of the individual well’s parameters and the operational characteristics of the available lift systems. For the different pumps and lift systems available to the oil and gas industry, there are unique operational/engineering criteria particular to each system, but they all require similar data to properly determine application feasibility. Such as the inflow performance relationship, liquid production rate, Gas liquid ratio, water cut, well depth, completion type, wellbore deviation, casing and tubing sizes, power sources etc. Each of the artificial lift systems has economic and operating limitations that rule out its consideration under certain operating conditions. An extensive overview of artificial lift design considerations was presented by Clegg et al. (2007). Clegg mentioned some economic factors such as: revenue, operational and investment costs as the basis for artificial lift selection. Ayatollahi et al., (2008): Selection of the proper artificial lift method is critical to the long-term profitability of the oil well; a poor choice will lead to low production and high operating costs. For the purpose of this thesis, Gas lift method will be considered with a view to optimizing production from an oil well and hence optimal production from the field.

During the primary stage of production, existing natural reservoir pressure may not be sufficient to cause fluid flow from the reservoir into the wellbore region through the production tubing to surface facilities; this might probably be due to the viscous nature of the oil (i.e. high viscosity). This inadequacy of the reservoir energy to lift the produced reservoir fluid from the wellbore to the surface may be caused by the viscous nature of the fluid or due to the hydrostatic head. For these reasons, an artificial lift system installation is often considered during the development of a well or field.

There are some drawbacks to operating a gas lift system above or below the gas injection rate. If the gas injection rate is low, the full gas lift potential is not utilized, resulting in inefficient operation of the gas lift valve. Furthermore, a pressure surge in the production facility will occur if the injection rate is too high, making production control difficult.

Optimization of gas lift system using commercial software is usually complex and time consuming which requires much dataset or parameters but, in this study, machine learning shall be adopted which only requires key parameters that affect the gas lift system and the production rate.

The cost of deploying a licensed commercial tool for the purpose of optimization of gas lift system for improving oil production is capital intensive, especially for the marginal field operators. Hence, this study seeks to develop machine learning model to solve same problem.

2. Review of Literature

Ahmed et al. (2021) adopted ANN in this work depends primarily on wells’ actual test data obtained from test separator and measuring devices installed on both mobile test package, flow lines and gas lift lines. In addition, as ANN can deal with limited or faulty data while acting with data with uncertainty which is considered a proven advantage of ANN over any analytical conventional methods, down-hole data obtained from static and flowing surveys using down-hole memory gauges, production logging tools (PLT) using electrical line, reservoir rock and fluid properties obtained from PVT lab analysis and core lab analysis were used in this work to run different models to reach the optimum results with satisfactory accuracy. The input dataset 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.

Okorocha et al. (2022; 2020) looks into the impact of artificial neural networks on gas lift optimization to boost crude oil production. It reviews various production challenges involved in the production process and suggested that artificial intelligence or machine learning could be introduce to minimize challenges.

According to the World Bank report (2008), National Oil Companies (NOCs) control 90% of the world's oil reserves and 75% of the oil production. A majority of the fields belonging to this production comes from mature fields. With many of the oil fields having depleted with time, the operating wells do not have sufficient pressure at the bottom to drive the fluids to the surface. Under such cases, the wells need support through the means of artificial lift systems. Such a requirement only increases when the reservoir is depleted of gas, or under situations where the oil is very heavy and also in systems where the water cut is high.

Imran et al. (2018) recommended that gas lift is simple and easy to manage after implementation; while the ESP method is very complex and difficult to plan and implement. Also, ESP has a very short lift in the well with a common lift expectancy within 2- 3 years. Besides, the gas lift method requires full workover on the well; therefore, few numbers of wells or individual well are not economical for gas lift method.

Hisham and Vincent (2017) employed PROSPER software to design a continuous gas lift system to examine capability to overcome the well and reservoir conditions. A well was used to simulate the system in PROSPER. Their result indicates that the continuous gas lift application increases the liquid production rate up to 1,864.6 STB/d from a non-producing oil well. On the contrary, there is a limitation to the result obtained because before the design of the gas lift system, history matching would have been performed using a well test data, which is fully incorporated in this study.

Wang et al. (2002) worked on the application of production optimization technique for oil field operations and in that process, a procedure was developed for allocation of optimal rate of production, the rate of the lift gas, and the simultaneous connection of the wells with surface pipeline systems. The optimization algorithm adopted the Newton iteration for the reservoir simulator level in commercial scale. While Beckner and Davidson (2003) presented a reservoir model with integrated facility to solve the problem of optimal rate allocation in the facility model with quadratic programming sequential technique and also embedded in the model was the procedure to tackle conditions that are not feasible. Kosmidis et al (2004) presented a nonlinear optimization algorithm with mixed-integer to handle the challenges of optimizing a gas lift system in oil wells via a common flowline. To achieve their objectives, they adopted a variation of sequential linear programming techniques. Also, a multi-objective approach for gas lift optimization was developed by Ray and Sarker (2006) to maintain the quality of the solutions thereby eliminating the daily gas lift optimization problems.

Kosmidis et al (2004) consider a more general production system consisting of wells, manifold and separators, and modelling pressure in the flowline and facilities. The production optimization problem is model as a mixed integral nonlinear programming (MINLP) problem that look at pressure as a nonlinear function balancing the momentum of the flowlines. They propose a method for finding the local optimum of the MINLP program which solves a sequence of MINLP problem.

Rashid (2010) solved a gas lift allocation problem with gas constraint. He addresses the effect of iterations between wells by developing an algorithm that iterate until convergence on wellhead pressure. A simulator was used in the loop to validate results, test pressures and generate curves.

Campos et al (2012) established the main requirement for integrated production optimization of large-scale oil fields. In the paper they stressed the importance of accurate well models to predict coning effects and integration with real-time optimization algorithms to reach optimal operating conditions.

Djikpesse et al (2010) presented a study on the optimization of gas lift system under facilities constraints. It was noted that gas lift optimization is employed in the field to enhance production of mature fields with several reservoirs and multiple wells drilled on them with a shared surface production facility. They aimed at finding the point of optimal gas lift over the entire wells network and pipeline systems while identifying the constraints imposed by the conditions of the reservoir. The presented a novel and cost-effective techniques to handle the gas lift optimization problems and claimed that these problems are expensive and difficult to compute.

Carlos et al (2013) stated that artificial lift technology is employed in oil field when the reservoirs have lost their natural means of producing its content to the surface production facilities. Thus, to choose any of the available artificial lift techniques, the optimal rate of production of the wells must be determined first before deployment, thereafter, other factors such as initial cost, the operating cost, deferment of production etc. associated with overall failure of the system which is mostly predominate in the electrical submersible pump (ESP) where changes in the reservoir conditions affect its performance. Therefore, the factors mention above are some of the reasons ESP are not selected for a lifecycle economic evaluation and as such, gas lift presents a better option but cannot match the high rate of production offered by ESP installations. It is imperative to not that in developing a field or maximizing the value of the asset, an adequate choice of artificial lift method is key to the success of the field.

3. Methodology

3.1.Research Design

Data acquisition is the first step to every program and machine learning process. The acquired data from oil field in the Niger Delta were pre-processed and analyzed. Hence, the workflow for the machine learning design process for this study is presented in Figure 1.

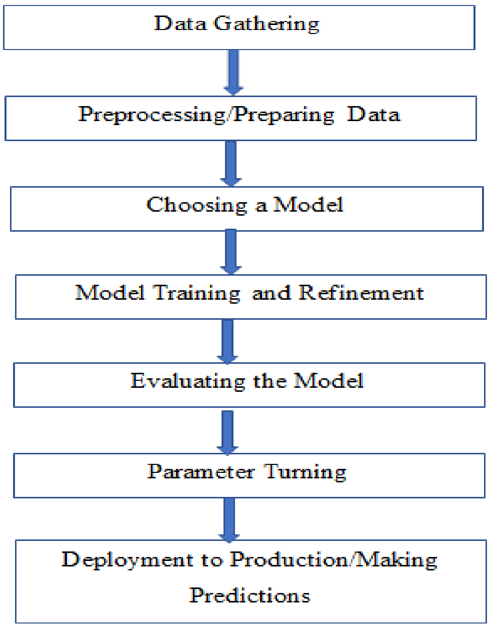

Figure 1 Basic step to using a machine learning.

For this study MATLAB was used to develop the machine learning algorithm to make predictions of the oil production rate with respect the gas lift gas injection rate and other key parameters as represented in Figure 2. Therefore, the MATLAB code to the algorithm is given in the appendix A of this thesis.

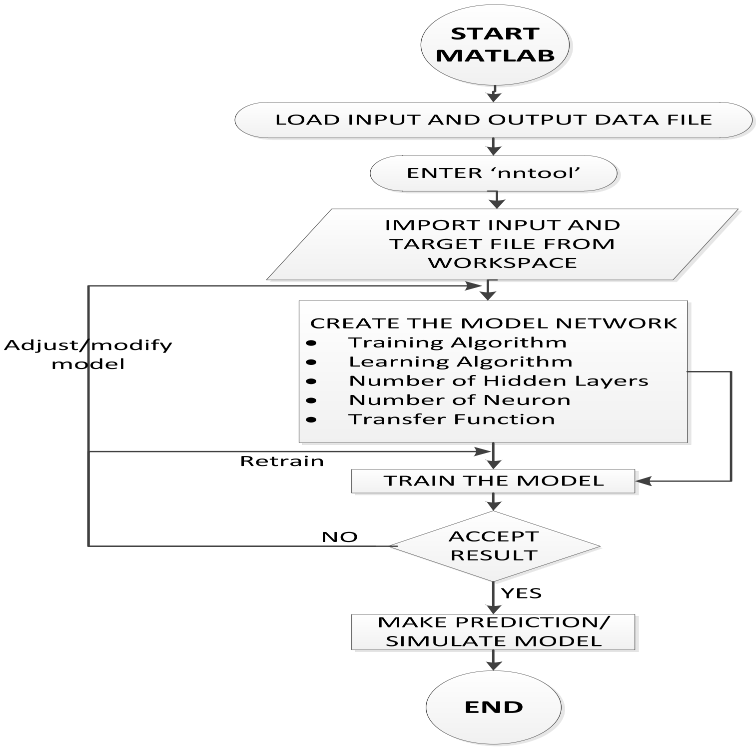

Figure 2 MATLAB flowchart for this study

In other to estimate the oil production rate, a two-layered feed-forward network with a tanh-sigmoid activated hidden neuron and a linear activated output neuron were used. The network was trained with a Levenberg-Marquardt back propagation algorithm. The architecture contains an input neuron with seven features which are the gas lift gas gravity, flowing top node pressure (psig), operating injection pressure (psig), gas lift gas injection rate(MMscf/day), depth of gas lift injection (ft), casing pressure (psig) and the water cut (%). Figure 3 is the proposed neural network architecture;

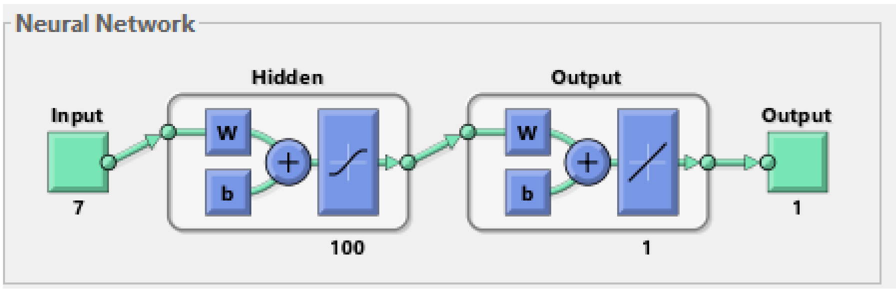

Figure. 3 Network Architecture

3.1.1 Tanh-Sigmoid Activation (Transfer) Function

The tanh-sigmoid activation function takes an input into a neuron which has value between plus and minus infinity and then squashes it to output a value between the range of negative one to positive one (-1 to 1). Mathematically, the tanh-sigmoid activation function is represented as;

$$let\ z = \Theta^T x \tag{1}$$

$$g(z) = \frac{2}{1+e^{-2Z}} - 1 \tag{2}$$

Where;

z = the vector product of the neuron weight transposed (Θ^T) and the input value (x).

g(z) = the tanh-sigmoid function.

This transfer function is commonly in back propagation networks, in part because its differentiable. Figure 4 illustrates the tanh-sigmoid function;

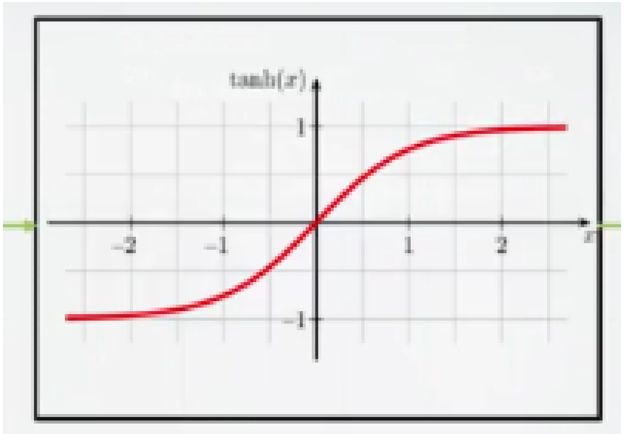

Figure 4 Graphic representation of the tanh-sigmoid transfer function

3.1.2 Linear Transfer Function

This function takes input to the neuron (in this case output from the tanh-sigmoid hidden layer) and turns it into a continuous number. Linear activation function calculates the neuron's output by simply returning the value passed to it. Mathematically, the softmax activation function is represented as

$$a = \text{purelin}(n) = \text{purelin}(Wp + b) = Wp + b \tag{3}$$

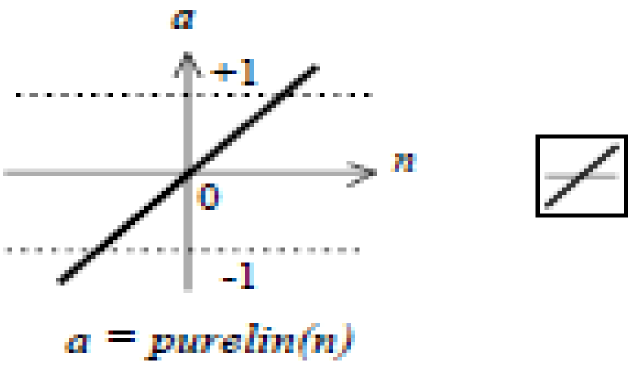

Figure 5 illustrates the linear transfer function;

3.1.3 Cost (Error) Function

The cost (error) function is the function used to minimize the error between the output (result by the network) and the target (reservoir response). Because parameter estimation is a multiple regression analysis problem that output continuous values Mean Squared Error cost function was used to train the network. The Mean Squared Error cost function given below;

$$J = \frac{1}{m}\sum_{i=1}^{m}(P(i) - y(i))^2 \quad (4)$$

Where

P is the model output of the training example i.
y = reservoir response of the training example i.

Fortunately, the mean squared error performance index for the linear network is a quadratic function. Thus, the performance index will either have one global minimum, a week minimum or no minimum, depending on the characteristics of the input vectors. Specifically, the characteristics of the input vectors determine whether or not a unique solution exists.

3.1.4 Levenberg-Marquardt (LM) Algorithm

The Levenberg-Marquardt (LM) algorithm also known as the damped least-squares method, is used to solve non-linear least squares problem. It is a combination of two methods: the gradient descent and the Gauss-Newton. Both the Gradient Descent and Gauss-Newton methods are iterative algorithms, which implies that they use a series of calculations (based on guesses for x-values) to find a solution. The gradient descent differs in that at each iteration, the solution updates by choosing values that make the function value smaller. More specifically, the sum of the squared errors is reduced by moving toward the direction of the steepest descent. At each iteration, the LM algorithm chooses either the gradient descent or Gauss-Newton and updates the solution.

The iterative update is dependent on the value an algorithmic parameter, λ, a non-negative damping factor which smooth's out the graph. The update is Gauss-Newton if λ is small (i.e. close to the optimal value) and a gradient descent if λ is large. The Gauss-Newton is more accurate and faster than the gradient descent when close to the minimum error. Therefore, so the algorithm will migrate towards the Gauss-Newton algorithm as soon as possible.

Parameter Estimation Training Procedure

The procedures with which the network was trained can be summarized in the following steps;

i. Import or read the training data (time and pressure data of the well test) from excel data sheet to MATLAB as variables.
ii. Choose the training algorithm in this case the Levenberg-Marquardt backpropagation.
iii. Choose the number of neurons in this chase one hundred (100).
iv. Pre-process the input data to prevent outliers
v. Divide the input data randomly into three parts for training, validating and testing of the algorithm (in this the case the division was made in the ratio of 70:15:15) to prevent over fitting.
vi. Select the cost or error (in this case the Mean Square Error) function to be minimized.
vii. Train the network to meet the goal (until the cost function is minimized and the variables converge).

3.2 Method of Data Collection

Table 1 serves as a comprehensive repository of data, encapsulating the dataset extracted from the initial five wells under consideration. The table functions as a structured and organized presentation of information, providing a systematic overview of key parameters, observations, or measurements associated with each well. This dataset is crucial for the ongoing research or analysis, offering a foundational understanding of the characteristics, behaviors, or conditions of the wells in focus. The arrangement of data in Table allows for easy reference, comparison, and analysis, enabling researchers, scientists, or stakeholders to draw insights, identify patterns, or make informed decisions based on the specific data points provided for each well. In essence, Table 1 serves as a valuable tool for anyone engaging with the dataset, offering a clear and concise format to comprehend, interpret, and leverage the information gleaned from the initial five wells in the study.

Table 1 Well and reservoir parameters for the first five wells

Parameter	**Well 1**	**Well 2**	**Well 3**	**Well 4**	**Well 5**
Gas lift gas gravity	0.8	0.78	0.8	0.64	0.72
flowing top node (psig)	250	250	200	217	500
operating injection pressure (psig)	1900	1900	1287.49	1145.36	1800
Gaslift gas injection rate (MMscf/day)	7.814	9.3	5.942	1.0	2.804
Depth of gas lift injection (ft)	13000	13500	7500	4183.7	6500
casing pressure (psig)	1180	1879.4	1369	1136	2254
WOC (%)	20.3	50	80	12	70
Oil production rate (stb/d)	4430.2	4300	1430.99	1748	868.4

The machine learning (ML) used in this work is primarily based on actual test data from wells obtained from test separators and measuring devices installed on both mobile test packages, flow lines, and gas lift lines. Furthermore, because ML can deal with limited or faulty data while acting on data with uncertainty, which is considered a proven advantage of ML over any analytical conventional methods, downhole data obtained from static and flowing surveys using downhole memory gauges, production logging tools (PLT) using electrical line, reservoir rock and fluid properties obtained from PVT lab analysis, and core lab analysis were used in this work to run different models to recalculate reservoir rock and fluid properties.

The input data set was divided into 70% for training, 15% for validation, and 15% for the primary test at random. The training data are used to improve the network based on their error. Validation data are used to assess network generalization and to halt training when generalization no longer improves. Because test data has no effect on training, it provides an independent measure of network performance during and after training. Data such as the gas injection rate and depth of gas injection would have been required to effectively model the unique behaviour in gas-lift wells.

In a compilation of more than 180 wells, none of the gas-lift well records provided this information. A neural network to predict the temperature profile in gas-lift wells was not developed due to a lack of comprehensive gas-lift well records for training and testing. All gas and gas-lift well data were discarded. In addition, due to the presence of outliers and anomalies, the database was reduced to 50 wells from various fields. Table 3.2 shows the data ranges that include the minimum and maximum values of the input element parameters assigned in various generated ML models.

Table 2: The data range for the parameters used in the ML model.

Parameter	Minimum	Average	Maximum
Gas lift gas gravity	0.64	0.744	0.80
Flowing top node (psig)	200	14393.92	50000
Operating injection pressure (psig)	1145.36	81566.49	190000
Gaslift injection rate (MMscf/day)	1	272.44	930
Depth of gas lift injection (ft)	4183.70	453389.08	1350000
Casing pressure (psig)	1136	79314.78	225400
Water cut (%)	12	2360.73	8000
Oil Production rate (stb/d)	868.40	129554.86	443020

4. Results and Discussion

The cleaned data is then organized and presented in a structured manner in Table 3. This table serves as a visual representation of the refined dataset, providing a comprehensive overview of the monthly data mean values. Each column likely represents a specific variable, and each row corresponds to a particular month, showcasing the calculated means. This presentation ensures clarity and accessibility for readers who seek to understand the aggregated monthly trends. This process involves determining the average value of each variable for every month over the specified period (January 2018 to December 2019). Monthly means are valuable for identifying trends, patterns, or variations in the data on a more manageable scale, facilitating a nuanced understanding of how variables evolve over time.

Table 3 Mean Monthly well data

4.2 Training Parameters

	Well1 THP (Psi)	Well1 Production Rate (BBL/D)	Gas Compressor Injection Pressure (PSI)	Gas Compressor Suction Pressure (Psi)	Well2 THP (Psi)	Well2 Production Rate (BBL/D)	Gas Compressor Injection Pressure (PSI)	Gas Compressor Suction Pressure (Psi)
1	88.6	698.6	1352.1	34.1	119.9	864.7	1294.4	34.5
2	84.6	648.0	1344.7	34.0	119.8	435.3	1289.7	34.3
3	70.6	562.1	1361.8	33.9	120.5	862.9	1291.1	34.1
4	70.6	664.8	1345.3	34.7	120.7	863.1	1290.7	34.7
5	76.0	1009.4	1341.0	34.5	120.8	434.8	1291.2	34.4
6	86.7	648.3	1365.1	33.5	100.9	834.5	1244.1	34.7
7	99.2	990.3	1277.3	34.1	101.0	880.1	1241.3	34.7
8	80.6	643.7	1295.9	34.0	102.0	884.8	1242.5	34.2
9	84.5	869.5	1257.4	34.1	90.3	435.2	1243.1	34.3
10	61.6	648.8	1278.9	34.7	86.0	430.0	1240.7	34.6
11	71.6	562.8	1263.8	33.6	99.6	441.5	1248.3	35.2
12	65.2	561.9	1261.1	34.4	101.7	668.2	1257.5	34.8
13	40.8	464.0	1260.3	32.2	111.9	403.0	1250.3	33.3
14	40.5	631.5	1275.5	33.8	113.7	439.1	1252.8	34.6
15	41.1	702.2	1243.3	33.7	113.9	420.1	1254.6	35.0
16	41.2	458.9	1262.4	33.6	113.0	452.7	1265.0	35.0
17	49.3	780.3	1254.7	34.2	119.9	475.7	1269.7	35.1
18	50.7	377.8	1253.0	34.7	121.1	454.3	1266.4	35.1
19	50.8	379.9	1254.0	34.5	121.0	454.8	1246.6	35.1
20	50.7	374.0	1242.8	34.6	121.3	454.7	1267.2	35.2
21	58.6	832.9	1220.9	32.3	71.0	785.2	1255.4	34.1
22	61.9	385.7	1283.5	34.6	66.7	348.0	1254.5	34.3
23	61.7	386.1	1283.1	35.2	66.6	347.2	1254.5	34.8
24	63.0	837.9	1290.6	34.6	66.5	754.4	1254.8	35.2

The success of machine learning algorithms used in this study depends on a wide range of contextual parameters as shown in Table 3.2 of the previous chapter. This is the model's set of learned features, which were formulated from the training data. The parameters of the machine learning model determine the specifics of the data transformation. A good model is one that can generalize to new, unknown data while maintaining high accuracy on either production or test data. Hence, after the gaslift model recognition training period, the following results were derived.

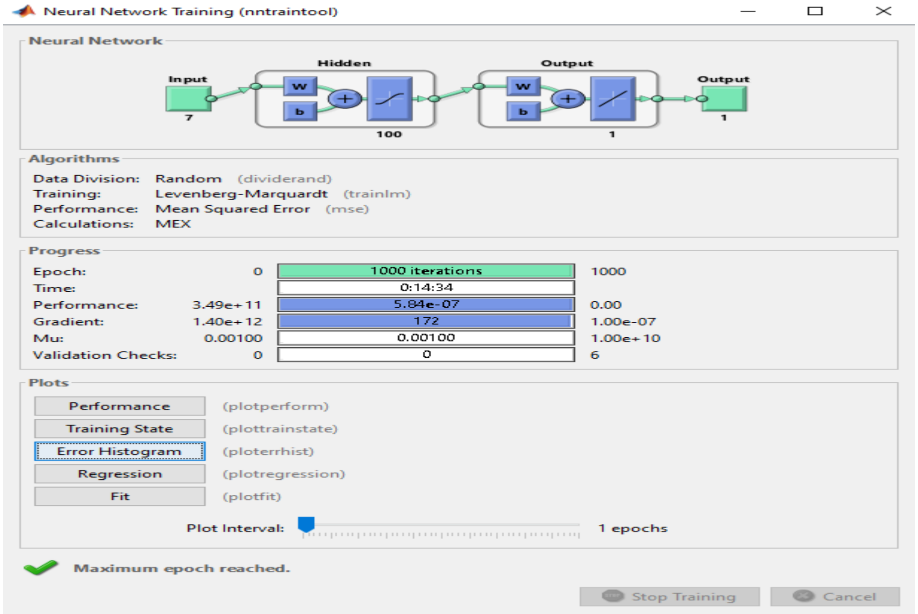

Figure 6: Training parameters

The training process using Levenberg-Marquardt algorithm for the model recognition took 14 minutes, 34 seconds to complete the entire iterations. as shown in Figure 6 of the performance (error function) of the algorithm. This optimal performance point is also known as the convergence point or the global minimum.

4.3 Model Validation

Validation is the procedure of checking the accuracy of a model. Your model's success in training does not guarantee success in production. Always divide your data in half, one for training and one for testing, before attempting model validation. Thus, a maximum of 0.00468 is shown in the error histogram (shown in Figure 7) depicting the discrepancy between the input and the output.

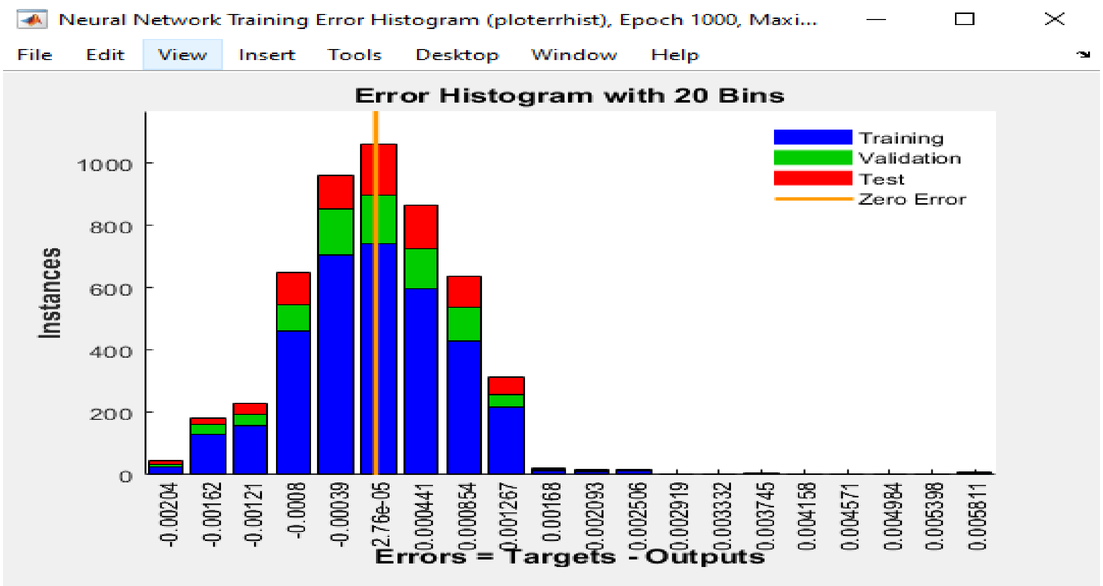

Figure 7 Estimation error histogram

4.4 Gas lift model recognition confusion matrix

The algorithm's confusion matrix is depicted in figure 8; the training confusion matrix shows that the algorithm properly identified 25.7% (721) of the training data as belonging to class 1, while misclassifying 0.1% (2) as belonging to class 3. On the other hand, 26.5% (694) of the training data was correctly classified as class 2 by the algorithm, while 0.2% (5) was incorrectly labelled as class 3. More than a quarter (24.6%; 690 instances) of class 3 data in the training set was accurately labelled as such. In addition, 24.6% (689) of class 4 training data was accurately labelled as such, whereas 0.1% (2) was incorrectly labelled as class 3. As a result, the algorithm had a 99.7 percent success rate throughout training. Algorithms are validated and tested to ensure they are not over-fitted and can be used effectively over a wide range of data. To test an algorithm, one merely presents it with data it has not previously seen. The final validation accuracy was 99.3%, whereas the test accuracy was 99.1%. This resulted in a classification (gaslift model recognition) accuracy for the algorithm of 100%.

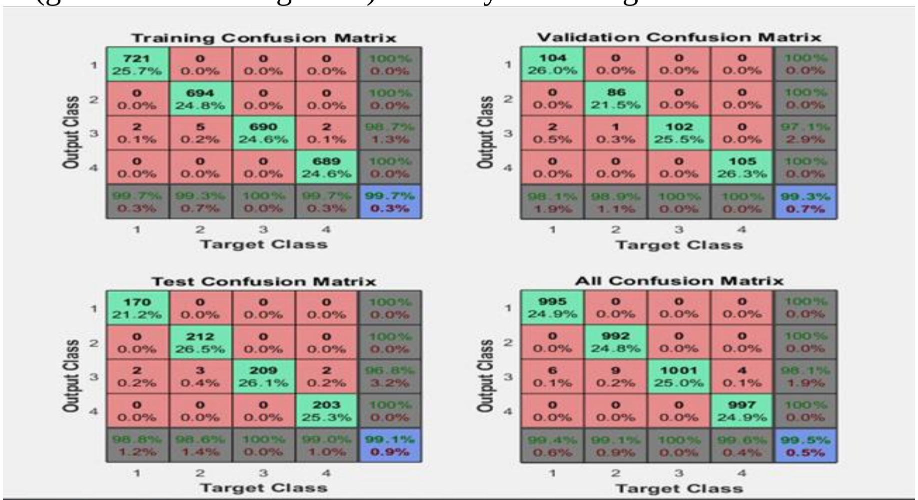

Figure 8: Algorithm's confusion matrix

4.5 Reservoir Model Parameter Estimation Training Results

The model parameter estimation algorithm was trained separately for the four different gaslift models that were covered in this study. The Figures 7 and 8 illustrates the results for class 1 only. After the training process, error and index of fitness for the different wells are shown in Table 3. Figures 7 display error histograms that are very close to the actual data for the three targets of well fluid rate, bottom hole flowing pressure, and optimal gas injection rate, respectively, resulting in a very good estimation in the real-time data. The training, validation, and testing regression values all look extremely near to one, with the highest value reaching 1.00, which can have an effect on how well the neural network is taught to perform.

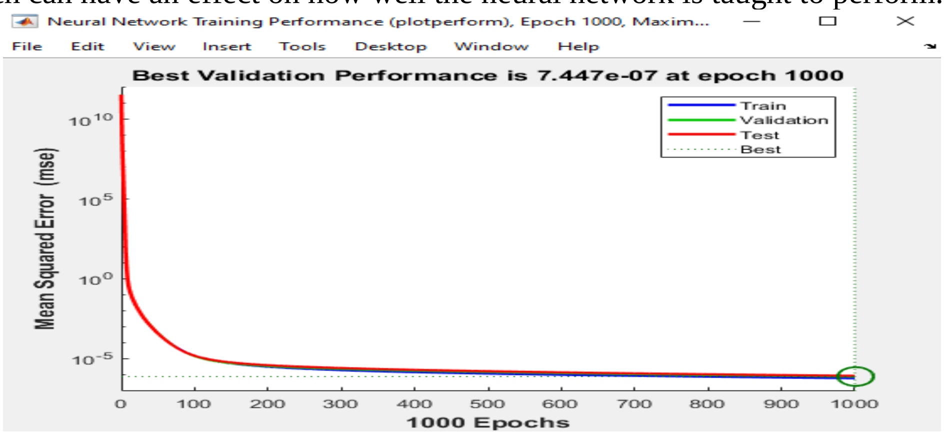

Figure 9 Mean square error change as number of iteration changes

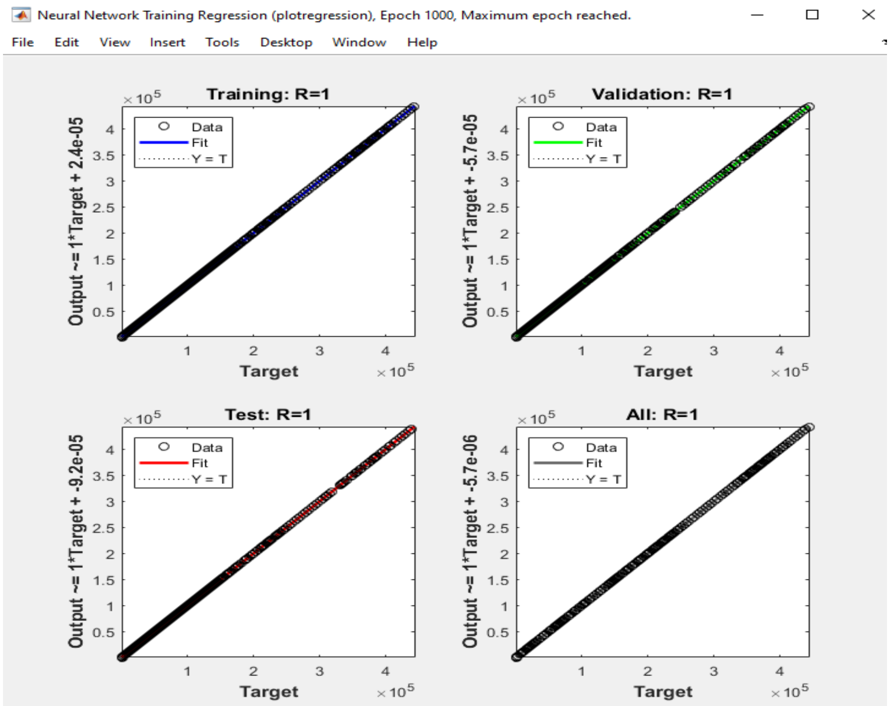

Figure 10 Regression plot

The available data was split into training, validation and test data in a ratio of 70:15:15. The algorithm took fourteen minutes and thirty-four seconds to parameter estimator. After the training process, me error and index of fitness is show in Table 4.

Table 4. Mean square error and index of fitness

TRAINING		**VALIDATION**		**TESTING**	
MSE (10^{-7})	**R**	**MSE** (10^{-7})	**R**	**MSE** (10^{-8})	**R**
5.84448	1	7.44698	1	8.24107	1

Table illustrates that the error from the training, validation and testing of the algorithms are minimal and also that they have an index of fitness of 1 which indicates a perfect fit.

5. Conclusion

The integration of machine learning into the analysis proves to be a powerful tool for real-time decision support and parameter estimation. The algorithm's high accuracy rates, as evidenced by the confusion matrices and parameter estimation results, showcase its effectiveness in recognizing gas lift models and accurately estimating parameters. This success in model training, validation, and testing phases underscores the model's ability to generalize to new, unseen data, providing a reliable framework for on-going decision-making in oil well operations. As the gas lift system plays a pivotal role in oil production, the findings from this comprehensive analysis contribute not only to a deeper understanding of the system's dynamics but also offer practical implications for optimizing operational strategies and improving overall efficiency in the oil and gas industry.

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