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Prediction of Liquid Accumulation in Gas Wells to Forecast the Critical Flowrate and the Loading Status of Individual Wells

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ABSTRACT: Liquid accumulation is a major problem in gas wells. The inability of gas to lift coproduced liquids to the surface imposes back pressure on the reservoir, limits the ultimate recovery and ultimately kills the well if improperly managed. Therefore, accurate prediction of its occurrence and reliable monitoring strategy is key to effectively handling liquid accumulation in gas wells. In this study, machine learning algorithms were used to develop regression and classification models to accurately predict the critical flowrate and the loading status of individual wells. The regression models used are the feed-forward neural network and a least squares support vector machine models while the decision trees model was used as the classification model to characterize the loading status of the wells investigated. These models were validated using actual published data and it was observed that the feed-forward neural network performed better in predicting the critical rate compared to the least squares support vector machine model with an R^2 value of 0.9833, and thus was adopted. The feed-forward neural network model was further compared with other critical rate models; and a consistent result with least percent error of 5.571% was also observed. Form this study, it is obvious that the neural network model provide benefits and good prospects in investigating liquid loading phenomena in gas wells compared to empirical models that apply so many simplifying assumptions.

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At the onset of production of gas from gas reservoirs, only single phase gas is produced (Ezekwe, 2011). However, as operating conditions fall below the dew point, a liquid phase in the form of condensed hydrocarbon or water or both is coproduced with the gas. At early stages of production, particularly in the mist flow regime, the flowrate of the gas is high enough to lift the coproduced liquids along with it to the surface. Howbeit, as the pressure of the reservoir declines, the gas carrying capacity of the coproduced liquid also decline. The decline in the gas carrying capacity (flow rate) causes liquids entrained in the core of the gas or deposited on the wall of the pipe, fall and accumulate at the bottom of the wellbore (Lea *et al.*, 2008). The accumulation of these liquid(s) at the bottom of the wellbore following the inability of the gas to transport them to the surface is what is termed liquid loading (Shekhar *et al.*, 2017). Liquid loading can occur in all gas reservoirs but it is most prevalent in wet gas reservoirs (Joseph *et al.*, 2013). The accumulation of liquids creates a back pressure on the adjacent formation, causes metastable flow, rapid decline in flow rate, abnormal rise in casing pressure, slugging flow and can eventually kill a well (Bolujo *et al.*, 2017, Ikpeka and Okolo, 2019). Hence, early detection is key to resolving it to prevent these problems associated with it. Over the years, curative and preventive methods have been developed to mitigate the adverse effects of liquid loading in gas wells. Typical curative techniques are the use of velocity strings, plunger lift, foaming of the liquid, gas lifting, beam pumping and swabbing while preventive techniques involves the use of critical velocity models that predicts the onset of liquid loading, the film reversal models and the use of dynamic simulation (Ikpeka and Okolo, 2019, Li *et al.*, 2001, Luan and He, 2012). Turner *et al.* (1969) pioneered the investigation of liquid loading phenomenon in gas wells. They developed two models, film-movement model and the entrained liquid drop movement model to predict the

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critical velocity for the onset of liquid loading. When these models were validated against field data, it was observed that the entrained liquid-drop movement models gave a better prediction than the film movement model, thus the droplet model became the preferred model for predicting the minimum velocity. Unfortunately, Turner *et al.* (1969 observed that even the droplet model under-predicted the minimum velocity which they attributed to the use of drag coefficient for solid spheres to liquid and adjustments to incomplete field data used for the validation. Thus, to give better predictions, Turner *et al* recommended that the droplet model be adjusted to 20% upward to improve its accuracy in predicting the minimum velocity.

Coleman *et al*. (1991), tested Turner et al model and confirmed the model as a good and reliable predictor of liquid loading in gas wells, however, stated that the adjustment of 20% upward was unnecessary for wells operating below 500 psi. Nossier *et al*. (2000) argued that the major reason for the under-prediction of the critical velocity by Turner et al model was the exclusion of the impact of the flow regimes. Hence, they incorporated flow regimes and developed two models for the transition flow regime and highly turbulent flow regime in estimating the critical velocity. Although, the Turner et al model is a good predictor of liquid loading in gas wells, it cannot predict when the well will die (Oudeman, 1990). The impact of liquid droplet concentration and coalescence was also investigated and considered a major factor the influence the occurrence of liquid loading (Zhou and Yuan, 2010). The film reversal on the wall of the pipe was also considered as the primary cause of liquid loading (Luo *et al*, 2014, Barnea, 1986). Film reversal occurs following the impingement and deposition of liquid droplets from the core on the wall of the pipe, which eventually cause a gradual increase in the wall film thickness; which grows over time and attains a critical thickness beyond which it begins to trickle down and accumulate at the wellbore (Luo *et al*, 2014, Barnea, 1986). Another technique that has been explored in investigating liquid loading phenomena in gas wells is the approach of dynamic simulation. By coupling thermodynamic and hydrodynamic models with appropriate equation of state and constitutive equations, the occurrence of liquid loading have been thoroughly investigated (Joseph and Hicks, 2018). Though with its inherent shortcomings, the dynamic simulation approach is considered more appropriate over critical velocity and film flow reversal models as the model is more encompassing. Each thermodynamic property that contributes to the condensation of liquids is investigated and monitored in space and time as the accumulation of liquids deteriorates. Moreover, the different flow regimes can be captured independently and used to properly describe the system as flow changes occurs during the accumulation of liquids instead of assuming a dominant flow regime throughout the productive life of a gas well (Dousi *et al.*, 2006). In order to improve the prediction of liquid loading, diagnostic models are now developed. Ansari *et al*. (2018) developed a smart model for real time diagnosis of liquid loading in shale gas using machine learning. By using supervised and unsupervised machine learning algorithms, the onset of liquid loading was identified in shale gas systems and their model showed a great promise in the prediction of liquid loading. The K-Means clustering model was used to help predict the loading and unloading status of wells.

Following the discrepancies among the variants of Turner *et al* model, there is the need to develop a smart model that can accurately predict the onset of liquid loading. Hence, in this study, three machine learning algorithms were used to develop a smart model that could give precise and accurate prediction of the critical conditions for the onset of liquid loading in gas wells using data obtained from Coleman *et al* and Turner et al. The algorithms used are: Artificial Neural Network (Feed Forward), Least Squares Support Vector Regression and Decision Tree algorithms respectively. Following the discrepancies among the variants of Turner et al model, there is the need to develop a smart model that can accurately predict the onset of liquid loading. Hence, in this study, three machine learning algorithms were used to develop a smart model that could give precise and accurate prediction of the critical conditions for the onset of liquid loading in gas wells using data obtained from Coleman *et al* and Turner *et al*. The algorithms used are: Artificial Neural Network (Feed Forward), Least Squares Support Vector Regression and Decision Tree algorithms respectively. Therefore, the objective of this paper is based on the prediction of liquid accumulation in gas wells using machine learning algorithms to develop regression and classification models to accurately forecast the critical flowrate and the loading status of individual wells. Therefore, the objective of this paper is based on the prediction of liquid accumulation in gas wells using machine learning algorithms to develop regression and classification models to accurately forecast the critical flowrate and the loading status of individual wells

MATERIALS AND METHOD

Two types of machine learning models were used to develop the models, a classification algorithm and two regression algorithms. The classification model was developed to give real time indication of state of the well considering the existing conditions. For this purpose, Decision trees algorithm was used while the regression models were developed to indicate the critical rate for a producing well and this was achieved using the continuous variable algorithms such as Feed-forward Neural Network and Support Vector Regression respectively.

To develop the classification model, 102 data sets from different wells with their loading status obtained from Turner *et al*. (1969) was used while the regression models were developed from data sets obtained from Coleman *et a*l. The data from Coleman *et al* contain 56 data sets from different wells with their critical flowrates; and these were used to train the regression models. For the regression models, the characteristic threshold velocity to be obtained was the target variable while the loading status of the individual wells was the target variable for the classification model. The main idea behind the classification model is to help operators monitor increasing liquid density as liquids accumulate at the wellbore to discern the status of the well. Tables 1 shows statistical summary of data from Turner et al showing the status of being loaded or unloaded while Table 2 shows statistical summary of data from Coleman *et al* used for the analysis.

Table 1 Statistical description of dataset for loaded and unloaded wells [9]

	Depth [ft]	WHP [psia]	Oil Gravity	Oil make [bbl/d]	Water make [bbl/d]	Tubing ID [inches]	Test flow [bbl/d]	Status
count	106	106	106	106	106	106	106	106
mean	7498.547	2327.4	57.336792	28.74151	2.578302	2.459236	3920.83	1.292453
std	2275.509	1459.0	13.582554	35.63428	8.017006	1.14386	2531.341	0.792428
min	2250	108	0	0	0	1.75	400	0
25%	5934	1527.5	52.7	4.325	0	1.995	1986.5	1
50%	7410.5	2193.5	56.7	12.2	0	1.995	3406	1.5
75%	8690	3075.2	65	31.8	0.4	2.441	5101.5	2
max	11850	8215	71.7	130.8	45.1	7.386	11767	2

Table 2. Statistical description of dataset for neural network prediction [10]

	Gravity	Depth [ft]	Condensate [bbl/d]	Water [bbl/d]	WHFP [psia]	qc [bbl/d]
count	56	56	56	56	56	56
mean	0.637875	6776.521	2.710714	4.276786	149.4286	524.28571
std	0.034548	1475.021	2.766204	4.72552	101.3064	190.87366
min	0.582	5.15	0	0	39	90
25%	0.61	6098.5	0	0	73.75	390
50%	0.628	6652	2.4	3.05	130	538
75%	0.66025	7864.25	4.075	6.625	183.5	636.25
max	0.75	9445	14.8	17.6	495	1072

Data Preprocessing: In the development of the neural network model, input data were preprocessed before performing the prediction to reduce noise, and also effect data normalization. The moving average smoothing filter was used to remove large peaks of data due to its simplicity and optimal performance in reducing random noise while retaining a sharp step (Smith, 1997). There was a slight difference in the tuning of the output variables for the classification and regression models. The regression models used continuous values, already contained in the dataset hence, no further tuning was needed. However, to develop the classification model, categorical data which could be read by the computer was needed. The output variables contained object data types which was unreadable. To convert the variables to readable form, categorical integers of 0, 1, and 2 were attached to the object variables. Near loaded wells were represented by 0, 1 was used to represent loaded wells and 2 was used to represent unloaded wells respectively. After normalization, smoothing, and categorization, the datasets were then made ready for training. The input-output variables were also prepared based on the type of model to be developed. The preprocessed data was then split into two. The first portion was used to train the model, and the second was used to test the models.

Development Of Ann Network Model: The training processes for the three models are similar. The data was read into the Python environment as a Dataframe using Pandas, a machine learning library. For the development of the ANN network model, sequential model was used to build in layers and add weight was created. A three-layer network was used in this work. The first layer consists of five neurons representing the input parameters (oil gravity, well depth, condensate make, and water make.). The second layer is the hidden layer, and the third layer contains one neuron representing, the output variables. The training group was split into two groups: the first was used to the train the network for the different algorithms and the second set was used to test for errors during the training for validation. This cross-validation process was used to monitor the performance of the network and prevent overfitting. Stochastic Gradient Descent (SDG), and mean absolute error were used as the optimizers and loss function for the development of the model.

RESULTS AND DISCUSSION

Two continuous variable models and a classification model was developed in this study and validated with field data. Figure 1 shows the prediction of the critical rate using the feed forward neural network against the observed critical rates from Coleman *et al* model. The blue solid line with a circular marker are the predicted critical rates while orange dashed line with square markers are the observed values. From Figure 1, there is good match from the Neural Network model in predicting the actual critical rate values.

Figure 2 shows the prediction of the critical rate using the Support Vector Regression model and again, was validated using data from Coleman *et al*. The predictions from SVR model is represented with blue solid lines with circular makers while the observed values are represented with orange dashed lines with square markers. As can be seen, from Figure 2, a close match was obtained as was seen in Figure 1. However, the accuracy of the models in the prediction of the actual values can only be ascertained from error analysis.

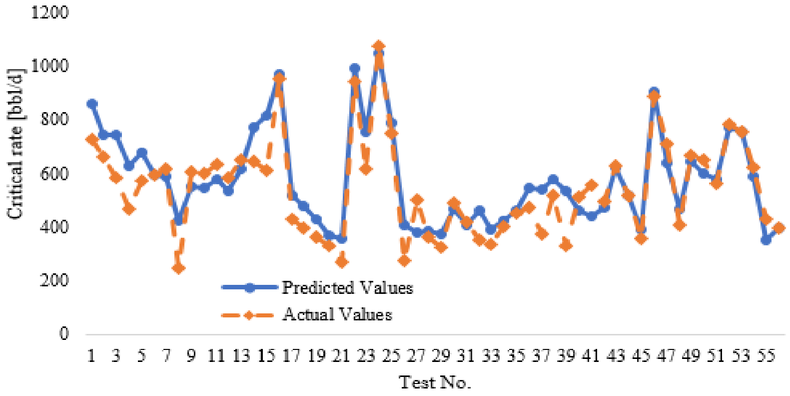

Fig. 1: Prediction of critical rates using Neural Network (blue solid line with circular makers) and observed critical rates from Coleman et al (orange dashed line with square markers), showing how close the Neural Network model predicted the actual critical rates.

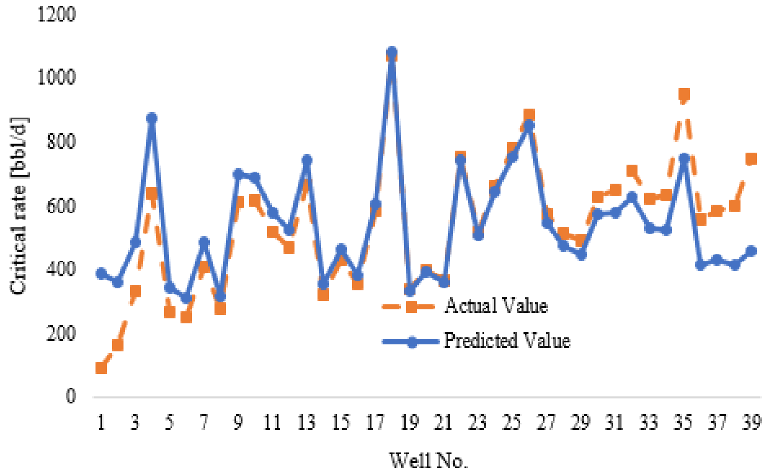

Fig. 2: Prediction of critical rates using the Support Vector Regression Model Showing (blue solid line) and observed critical rates obtained from Coleman et al (orange dashed line with square markers)

Unlike the regression models, the classification model was built using the data from Turner *et al*. (1969). This model was used to predict the status of a well whether it is loaded, near loaded or unloading in order to eliminate the dependence on critical velocity models in predicting liquid loading in gas wells as shown in Figure 3. From Figure 3, the model was able to accurately predict 81% of the status of the wells and differentiate them into loaded, near-loaded and unloading conditions respectively. However, it was observed that near-loaded conditions were not as accurately predicted as the loaded and unloaded conditions by the model. The model either over-predicted or under-predicted the near-loaded conditions in the investigation.

In order to ascertain the predictive capabilities of the models, an error analysis was carried out using mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE) and the coefficient of determination (R^2) as shown in Table 3. As can be seen in Table 3, the Feed Forward Neural Network model gave the best prediction with an R^2 value of 0.9833, followed by the Decision tree, with R^2 of 0.8152 and lastly, the Support Vector Regression model with R^2 of 0.7536 respectively. The Support Vector Regression model did not perform very well with the obtained data and this may be due to the SVR algorithm behaving like a classifier hence, causing a mix up whereas, the classification model also had a slightly low accuracy and this could be attributed to the limited data used for the analysis.

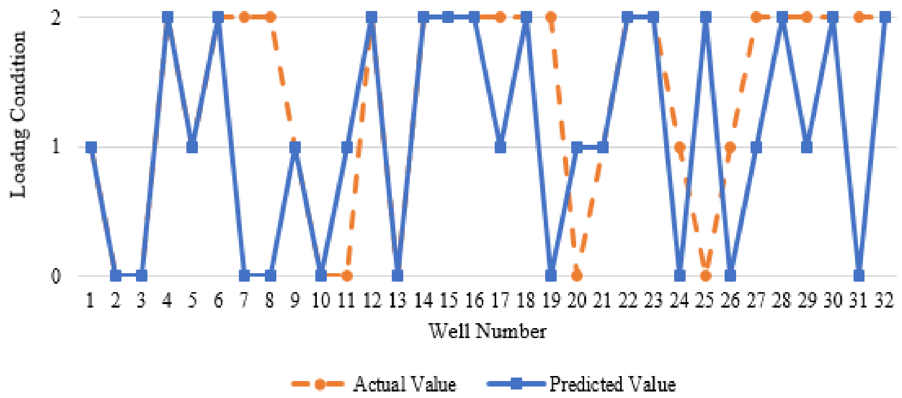

Fig. 3: Prediction of well status using the classification model. The blue solid line with square markers are the predicted status while orange dashed line with circular markers are the observed status obtained from Turner et al model.

Table 3: Comparison of the predictive performance of models

Models	MAE	MSE	RMSE	R^2
SVR	0.2450	0.3459	0.5881	0.7536
Neural Network	0.1667	0.0557	0.2360	0.9833
Decision trees	0.2813	0.2364	0.4862	0.8152

The Feed Forward Neural Network model was selected as the preferred model and compared with other critical rate prediction models as shown in Table 4. Table 4 shows the percent errors from each predictive model. The closer the value of the percent error to zero on the number line, the better. As can be seen in Table 4, the feed forward neural network is the best (5.571%), followed by Luan and He model (-6.073%), then Bolujo *et al* model (-9.126%), and Turner et al model (-12.344%). Prediction from Li et al model gave the highest percent error and the least accurate prediction of the actual critical flow rates observed with a value of 24.545%

Table 4: Comparison critical rate prediction models

Model	Percentage Error(%)
Turner et al Model	-12.344
Li et al Model	24.545
Luan and He Model	-6.073
Bolujo et al Model	-9.126
Neural Network	5.571

Conclusion: This study involved applying machine learning algorithms to investigate the onset of liquid accumulation in gas wells. Three machine learning models were developed using the feed forward neural networks, least squares support vector machine, and decision trees algorithms; these were evaluated using statistical metrics and validated with actual data from obtained from literature. From the error analyses, the feed forward neural network model gave the best degree of accuracy compared to the support vector machine. The classification model also gave a good degree of accuracy as it was able to predict about 81% of the status of wells being investigated.

NOMENCLATURE

ANN = Artificial Neural Networks
SVM = Support Vector Machines
SVR = Support Vector Regression
SDG = Stochastic Gradient Descent
Q_c = Critical Rate
WHFP = Wellhead Flowing Pressure
ID = Internal Diameter
MAE = Mean Absolute Error

MSE = Mean Squared Error
RMSE = Root Mean Squared Error
R^2 = Coefficient of Determination

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