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Research Paper

Smart System for Predicting the Flow Rate of Gas Using Linear Regression with Gradient Descent Algorithm

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Abstract- *Multiphase progression of oil, gas, and water in a similar line is normal marvels in gas and oil industry. Determining individual flow rates before reaching the separator is of great importance for production monitoring, optimization, and reservoir management. Liquid loading is the aggregation of fluids in the wellbore decay. It happens in vertical or veered off wells during production from gaseous petrol reservoirs as an outcome of buildup and mixture of fluid from gas streams. In other to prevent liquid loading, we developed a smart system for predicting the flow rates of gas in a gas well. The system was built using Linear Regression and Gradient Descent algorithm on a gas reservoir data. The dataset comprises of seven columns namely Time, CassingPressure, Flowrate, LinePressure, StaticPressure, TubingPressure and Qmin (Which is the greatest number of flows in the gas well. We pre-processed the data and selected few import features by means of feature extraction in training our proposed model. The model was evaluated in terms of R square, Root Mean Error and Mean Absolute Error, and accuracy. The R square had a value of 91%, which simply shows that around 91% of predicted variable can be describe by the model, and a training accuracy of about 99.2, Mean Square Error and Mean Absolute Error about 44921.09 26745.11.*

Keyword-*Flowrate, Reservoir Well, Linear Regression, Gradient Descent Algorithm, Gas*

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I. Introduction

Multiphase progression of oil, gas, and water in a similar line is normal marvels in oil and gas industry. Determining individual flow rates before reaching the separator is of great importance for production monitoring, optimization, and reservoir management. However, the use of common test separators to get these measurements is inadequate, and does not provide real-time monitoring. While utilizing complex multiphase stream meters (MPFMs) isn't yet attainable for well-level because of significant expenses, estimation vulnerability, and continuous disappointment especially when introduced down-opening [1]. The problem of the flows in multiphase is experienced across industrial applications. In nuclear energetics, the gas-liquid flows with phase transitions are formed in the process of reactor cooling. In the petroleum sector, the three-stage streams are shaped in the pipelines and wells. Such streams are regularly transient with all boundaries changing on schedule and in space [2].

Ordinarily, in the investigation of such issues one is keen on assessment of input parameters at specific areas (e.g., at the well base). This has been challenging since every one of the parameters advancing on schedule as indicated by the complex actual phenomena. In existing approach, the transient multiphase streams are concentrated on utilizing numerical demonstrating and mathematical simulations [3]. Improved observing of multiphase stream rates in gas and oil creation wells will empower operators for better diagnostics and moderation of the problems of production. For example, in a gaseous petrol wells, low measures of fluids (water, condensate) can prompt problems of production (fluid stacking, salt precipitation, and scaling). Precise assessment of this limited quantity of fluids could uphold operators for better dynamic. Right now gas and fluid paces of individual wells are gauges occasionally during a well test and the consolidated gas and fluid progressions of various wells are estimated of persistently at the creation separator [4].

A savvy approach is utilizing virtual stream meter (VFM), which is a delicate sensor that can assess continuous stage stream rates utilizing existing estimations, like pressing factor, temperature estimations and stifle valve opening percent. VFM can expand MPFM estimations and go about as a reinforcement when it falls flat [5]. On the other hand, it can give assessments between test separator runs if no MPFM is introduced. This eventually reduces functional and upkeep expenses just as supports incorporated tasks. VFM is normally evolved utilizing exact connections or robotic models, which both are subject to liquid properties, functional conditions, creation systems, and are touchy to evolving Gas-Oil proportion (GOR). Furthermore, robotic models are computationally costly, have intermingling issues, and include broad tuning on field information. Along these lines, it is proposed to utilize delicate registering strategies, which appear to be likely possibility to foster virtual stream meter. [6].

In other to prevent production problems in oil and production, we present a smart system for predicting the flowrate in a gas well using Recurrent Neural Network algorithm.

II. Related Works

Arash et.al. (2017) adopted four models, which comprises of both Machine learning and Deep Learning methods in predicting progressive production of gas along with proportionality of the initial flow rate and the total flow rate of gas. The models they applied are, Artificial Neural Network, Least Square Support Vector Classifier, Decision Tree and Adaptive Neuro Fuzzy Inference System. The results of the four models in terms of performance evaluation based absolute average relative deviation percentage are 6.95%, 8.95%, 14.66%, and 30.5% for Least Square Support Vector Machine, Decision Tree, Adaptive Neuro-Fuzzy Inference System, and Artificial Neural Network. The experimental result shows that the Least Square Support Vector Machine is best fit in predicting the progressive production of gas [7].

Khan et.al. (2019) made use of machine learning algorithms in developing a correlation model that can perfectly predict the rate of oil in a contrived gas wells lift. The algorithms used are Artificial Neural Network, Least Square Support Vector Classifier and Artificial Neuro Fuzzy Inference Systems. Their experimental results shows that Artificial Neural Network is more accurately in predicting the rate of flows in a gas well with an accuracy of about 99% [8].

AL-Qutami et.al. (2017) proposed a virtual flow meter (VFM) for estimating the flow rate of gas in multiphase production flow lines using Radial Basis Function Network. The model is confirmed with accurate well test estimation, and results gotten from their experiment shows promising performance. The proposed model conclusively provided a captivating and a low-cost solution to intersect the tracking of actual demands of production, and minimizes the cost of maintenance and running [9].

Ignatov et.al. (2018) proposed a model for predicting the flows of multi-phase wellbore using XGBoost. They trained their proposed model on the time line of various concrete constants generated using the numerical test system of the full-scale transient wellbore streams. As indicated by THEIR new experiment with complex wellbore setups and streams. The evaluation of the error shows that the forecast turns out to be especially difficult on account of profoundly transient slug streams [10].

Shoebi et.al. (2018) developed a calculative and structured models in determining the rates of production of liquid and gas in wells using an existing dignified data. They tested their proposed method on a field and simulated data from different gas wells using artificial neural networks. The experimental results shows that artificial neural network can perfectively estimate the rates of flows of multiphase in both field and simulated data [4].

Farsi et.al. (2021) applied an enhanced machine learning models on a dataset of 6292 records of data with an input parameters of seven relating to the flow of oil through 40 pipelines in addition to processing equipments in southwestern Iran in predicting a wide scope of oil stream rates through opening plate meters. They combined multi-layer perceptron and Distance-weighted K-nearest neighbor algorithms are with firefly (FF) swarm type and artificial-bee colony analyzers. The Distance-weighted K-nearest neighbor achieved the highest performance of root mean square errors of 8.70% for oil stream rate through the hole plates, subsequently eliminating reliance on inconsistent experimental recipes in such stream estimations [11].

Bikmukhametov and Jaschke (2019) adopted XGBoostalgorithm gives exact flowrate forecasts under different conditions, and it tends to be utilized as a back-up just as an independent multiphase stream metering solution. The performance evaluation of their model was carried out using the Mean Absolute Percentage Error [12].

Sanzo et.al. (2020) developed a framework using data driving metering technique in predicting the flowrate of gas and oil in a single well. Their proposed framework can be used in the optimization of the production of gas and oil management. The performance of their model was done using mean relative error, on which they achieved a mean relative error lower than 3% on an gas and oil well [13].

Khamehchi et.al. (2020) adopted two machine learning models namely pressuregradient method and genetic algorithm in estimating the two phase flowrate of gas and oil using a wellhead data The proposed pressure gradient strategy created dependent on unthinking methodology anticipated the stream rates more than the algorithm of genetic. Their work is being limited in using just some selected features and parameters [14].

III. Design Methodology

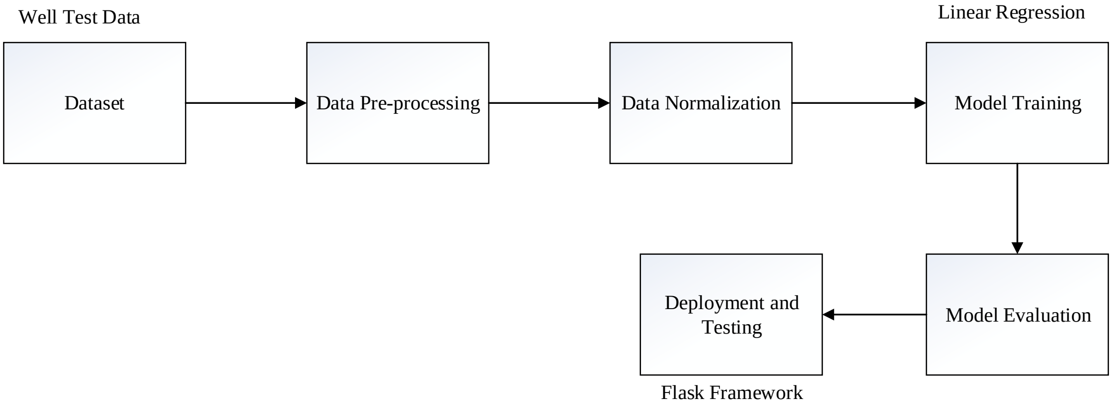

Figure 3.1 Architecture of the Proposed System

Dataset: For the purpose of this research we, will be making use of a well test data. The dataset comprises of seven columns namely, Time, CasingPressure, FlowRate, LinePressure, TubingPressure, StaticPressure, Qmin. The casing pressure is the force that is expected to penetrate pipes to keep an ideal control of the tasks that will be completed in the gas well, the flowrate is the sum of well creation rate in the gas well. The line pressure is the force expected to move the gas from the well fields to limited utilities. The tubing head pressure is the force on the tubing, that is estimated in the wellhead, and Qmin is the base flowrate in the gas well.

	Time	CasingPressure	FlowRate	LinePressure	StaticPressure	TubingPressure	Qmin
0	1437815718	515.764	315.083	289.940	287.979	235.035	105.083
1	1437815737	515.798	320.269	289.930	287.925	234.976	105.269
2	1437815916	515.890	309.478	290.479	288.598	235.251	105.478
3	1437816101	516.164	181.501	291.027	289.846	235.892	105.501
4	1437816459	516.256	194.514	290.753	289.416	235.159	105.514
5	1437816817	516.439	299.922	291.392	289.652	235.526	104.922
6	1437816997	516.622	321.522	291.667	289.967	235.709	105.522
7	1437817181	516.714	279.395	291.575	289.325	235.434	105.395
8	1437817360	516.989	254.534	292.032	289.915	235.984	105.534
9	1437817540	517.264	203.055	292.398	289.639	236.442	105.055
10	1437817719	517.172	313.807	292.854	290.931	236.992	105.807
11	1437818261	517.447	238.451	293.129	290.741	236.717	105.451
12	1437818440	517.630	305.950	293.677	291.217	237.541	104.950
13	1437818620	516.164	230.647	294.042	291.500	236.992	105.647
14	1437818799	515.890	327.666	293.860	291.727	237.358	105.666
15	1437818978	515.615	293.388	294.591	291.469	237.908	105.388
16	1437819157	517.630	210.913	294.042	291.242	237.541	104.913

Figure 2: Training Data for gas well

Data Pre-processing: In other to have a better training performing of our trained model, we will be need to make our data scalable and fit, In other to achieve this, we will be making use of standard scalar function in python.

Data Normalization: we will utilize numpy in making our preparation information to utilize a typical scale, without misshaping contrasts in the scopes of qualities or losing of data

Model Training: The model will be trained using Linear Regression algorithm. The model will be trained by passing 80% of the gas well data to the Linear Regression algorithm, and 20% of the dataset will be used for testing. In other to get a better training accuracy.

Model Evaluation: We will be making use of three evaluation metrics in evaluating our proposed Linear Regression Model in predicting the flowrate in gas wells. The evaluation metrics are Adjusted R square or R square, Root Mean Square Error or Mean Square Error and Mean Absolute Error. The mathematical representation of the metrics can be seen below:

$$R^2 = 1 - \frac{SS_{Regression}}{SS_{Total}} = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y})^2} \ldots \; equation\ (1)\ \ R\ Square\ Formula$$

The R square is determined by the total of Square of expectation mistake isolated by the absolute amount of the square which replaces the expectation with mean

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \; \ldots equation\ (2)\ Mean\ Square\ Error$$

The mean error is determined by the amount of square of forecast error substracted by the quantity of data points.

$$MSE = \frac{1}{N} \sum_{i=1}^{N} |y_i - \hat{y}_i|^2 \; \ldots equation\ (3)\ Mean\ Absolute\ Error$$

Mean Absolute Error is not quite the same as Mean Square Error by treating all errors similar while Mean Square Error gives a bigger punishment to large forecast errors.

Deployment to Web: We will be making use of flask framework in creating a mini web application that will be used in deploying the trained model to web.

IV. Result and Discussion

This paper presents smart system for predicting the flowrate in gas well using Linear Regression Algorithm. The system starts by acquiring a gas well data. The dataset comprises of seven columns namely Time, CassingPressure, Flowrate, LinePressure, StaticPressure, TubingPressure and Qmin (Which is the gretest number of flows in the gas well as shown in figure 1. The dataset was pre-processed by using StandardScaler() function in python in providing a well-balanced and standard values. After this process we normalized and selected few features that we will be using in training our model. The selection of features was done by means of feature extraction. The selected columns that we used in training our models are CassingPressure, Flowrate, LinePressure, StaticPressure, TubingPressure. The columns were selected as they play vitals rolls in determining the rate of flows in the gas wells. The selected data which is our training data was divided and assigned into two variables x and y, where the x variable holds the input data and the variable holds the output data which is the labelled class. The training data was then passed to Linear Regression algorithm in training a model for predicting the flowrate in gas well. The trained model was evaluated in terms of R square, Root Mean Error and Mean Absolute Error, and accuracy. This can be seen in figure 6 and 7. In figure 6 the R square had a value of 91%, which simply shows that around 91% of reliable variable can be describe by the model, and a training accuracy of about 99.2%. Figure 7 shows the metrics evaluation in terms of Mean Square Error and Mean Absolute Error, where we obtained a Mean Square Error to be about 44921.09 and Mean Absolute Error of about 26745.11. Figure 3 shows the corrections between pairs of values in the dataset. Figure 4 shows a histogram that represents the distributions of casing pressure and the rate at which the gas flows. Figure 5 shows the gradient descent curve of the training data. The gradient descent curve shows an iterative optimization in finding a local minimum of differentiable function. Figure 8 shows the smart system for prediction the flow rate in gas well and figure 9shows the predicted result of the system.

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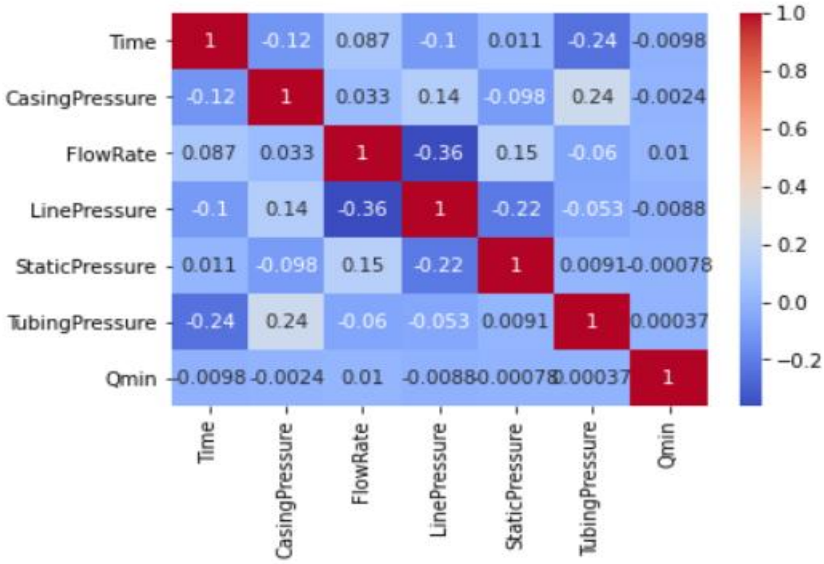

Figure 3: Correlation Metrics the dataset.

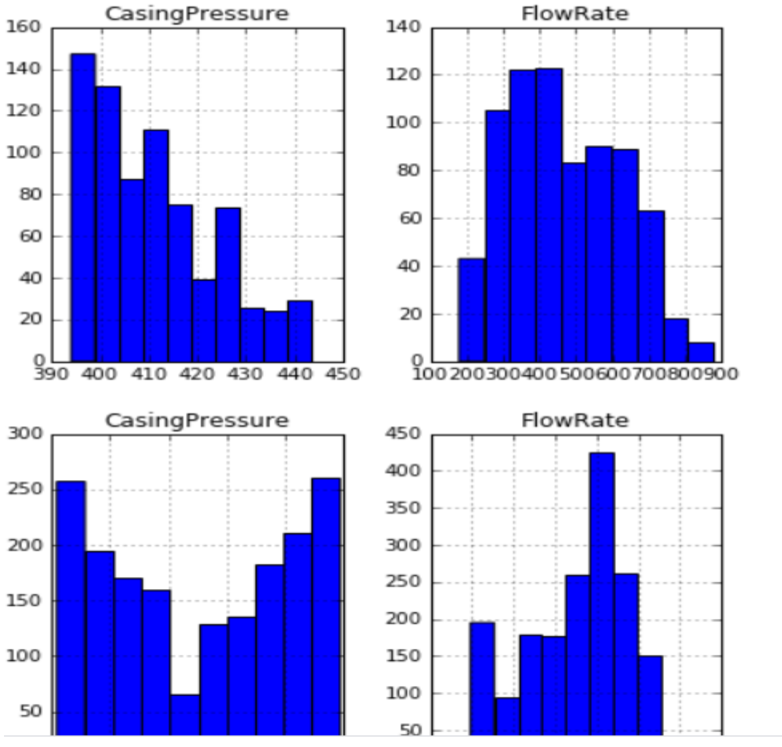

Figure 4: Distribution plot of Casing Pressure and Flow Rate

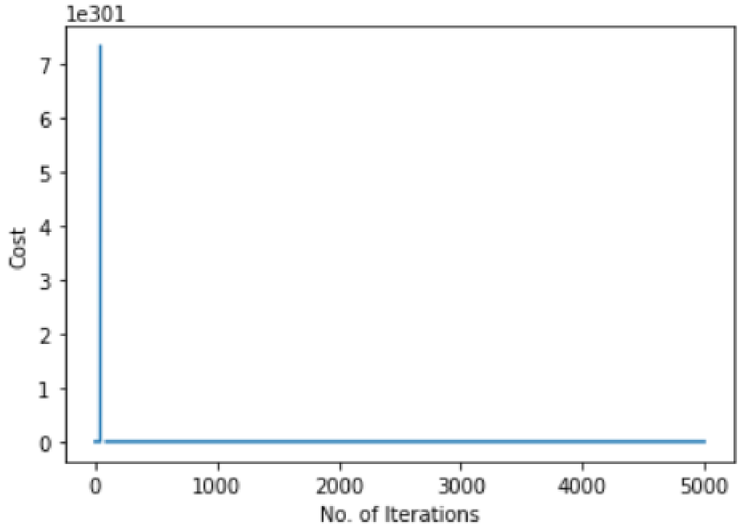

Figure 5: Gradient Descent Algorithm.

In other to have a better optimization in finding a cost on each iterative steps in the dataset, gradient descent algorithms was being used. Gradient Descent Algorithm was used for a better optimization of our training data.

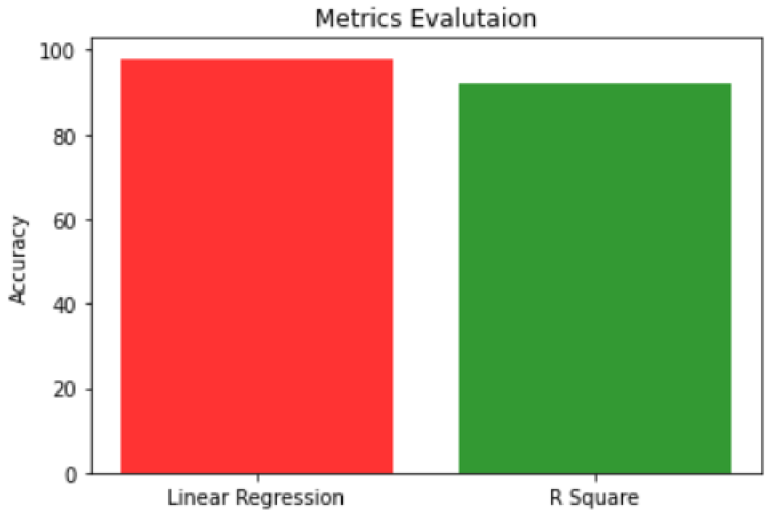

Figure 6: R Square Vs Linear Regression

This shows the accuracy result obtained by our trained model with and the metrics evaluation of R Square. Our proposed model had an accuracy result of about 99.2% and R square had

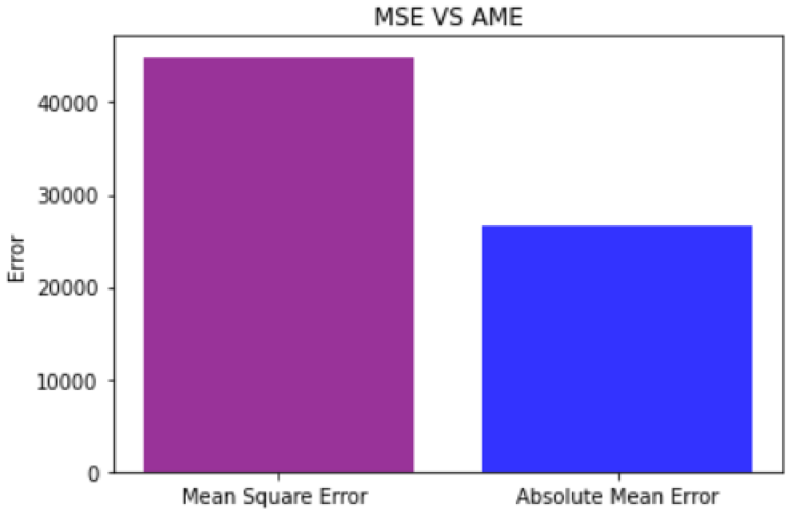

Figure 7: Mean Square Error Vs Absolute Mean Error
This shows the metrics evaluation of our proposed model in terms of Mean Square Error and Absolute Mean Square Error

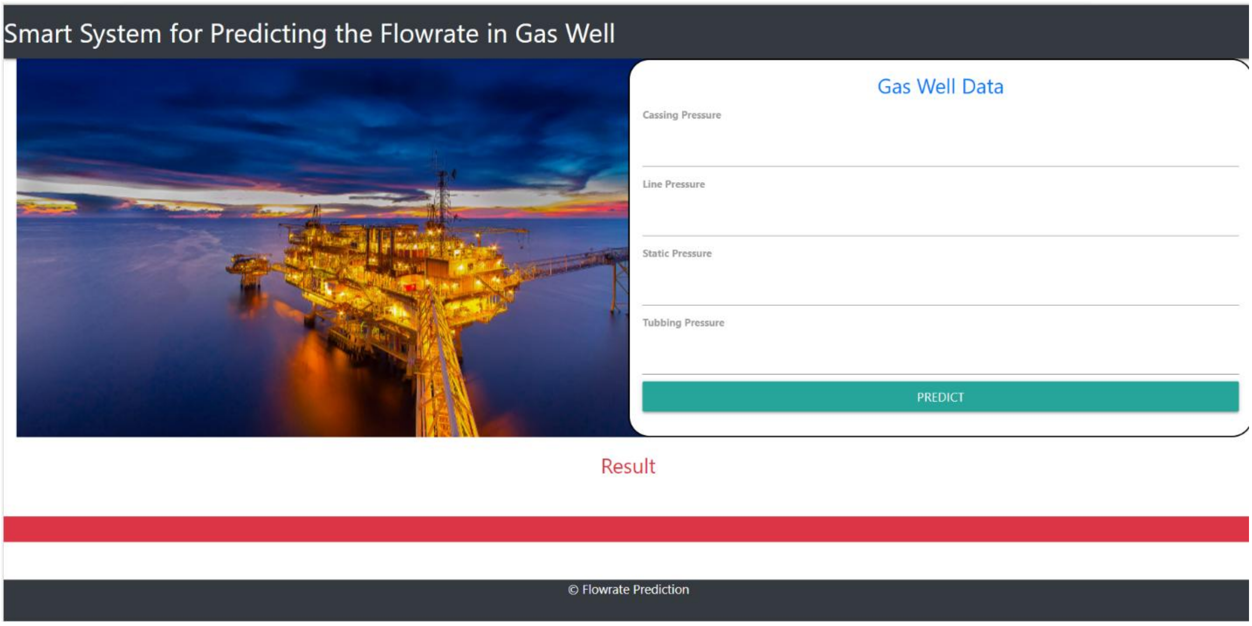

Figure 8: A web-based system for testing our deployed model.

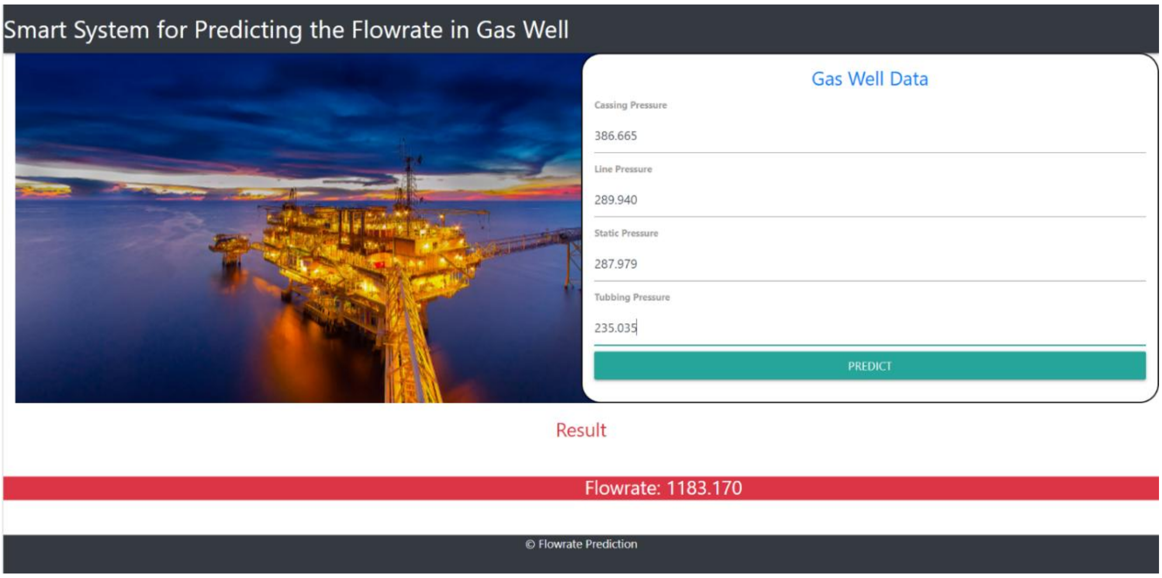

Figure 9: Predicted Result

The result shows that there is a proper flow of gas in the gas well.

V. Conclusion and Future Work

Liquid loading is the aggregation of fluids in the wellbore decay. It happens in vertical or veered off wells during production from gaseous petrol reservoirs as an outcomes of buildup and mixture of fluid from gas streams. In other to prevent liquid loading, we developed a smart system for predicting the flow rates of gas in a gas well. The system was built using Linear Regression and Gradient Descent algorithm on a gas reservoir data. The dataset comprises of seven columns namely Time, CassingPressure, Flowrate, LinePressure, StaticPressure, TubingPressure and Qmin (Which is the greatest number of flows in the gas well. We pre-processed the data and selected few import features by means of feature extraction in training our proposed model. The model was evaluated in terms of R square, Root Mean Error and Mean Absolute Error, and accuracy. The R square had a value of 91%, which simply shows that around 91% of dependent variable can be explained by the model, and a training accuracy of about 99.2, Mean Square Error and Mean Absolute Error about 44921.09 26745.11. The paper can be improved by using a Deep Learning Model for predicting Estimating the continuous flow of gas rate in gas well.

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