



Estimation of Well Flowing Bottomhole Pressure (FBHP) Using Machine Learning

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ABSTRACT - Flowing Bottomhole Pressure (FBHP) is an essential factor for oil well performance evaluation, but conventional measurement methods can be costly and lack real-time capability. This study presented a machine learning approach to estimate FBHP using simulated data from established vertical flow correlations (VLP). The proposed framework included four main steps: collecting input parameters, simulating pressure drops calculation, developing an artificial neural network (ANN) model, and designing the FBHP calculation algorithm. The ANN was developed using key input variables, including inlet pressure, system temperature, tubing size, inclination, segment length, gas-oil ratio (GOR), water cut, oil American petroleum institute gravity, gas gravity, fluid rate, and VLP type. A dataset of 790,409 points from several multiphase flow simulations was used, covering various well conditions for naturally flowing oil wells without artificial lift. The optimal ANN architecture featured six hidden layers and was trained with transformed, encoded, and normalized inputs, achieving a testing mean absolute error (MAE) of 7.8259 psia and R^2 of 0.9993. Segment-level predictions were then conducted iteratively to estimate FBHP for the whole well trajectory. Compared to earlier studies, the novelty of this work resided in its large and diverse set of well-flowing conditions, combined with comprehensive tubing geometry using segmentation. This approach enabled the modeling of a wider range of flow scenarios and complex well trajectories.

Keywords: flowing bottomhole pressure, artificial neural network, vertical flow correlation, well performance.

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INTRODUCTION

Flowing Bottomhole Pressure is one of the most important parameters for production engineers to monitor oil or gas well performance. FBHP provides crucial information to assess whether a well is operating normally or experiencing anomalies. Accurate FBHP monitoring not only supports production optimization but also advises decision making for well intervention and oil field development (Guo et al., 2007).

Some techniques are available to measure FBHP, depending on technical needs and economic feasibility. Installing permanent downhole pressure gauge is a modern solution that enables real-time monitoring but it is relatively expensive and typically suitable only for high-producing wells. As an alternative, periodic pressure surveys can also be conducted using wireline units equipped with Electronic Memory Recorder. While this method is less expensive than installing permanent gauge, it still involves significant costs and does not provide long-term real-time data (Schlumberger 1998).

A cost-effective alternative is to estimate FBHP using established vertical flow performance correlations, such as Beggs-Brill, Duns-Ros, Orkiszewski, and others. These correlations use surface pressure, flow rates, well geometry, and fluid properties to calculate pressure drops and estimate FBHP without requiring expensive downhole equipment or surveys. However, while this is only an estimation method, applying these correlations also requires detailed and complex procedures and also rely on the accuracy of input data. Estimation errors can occur if input parameters are inaccurate or flow conditions change significantly (Lyons et al., 2005).

Machine learning has become an increasingly popular tool in the oil and gas industry, supporting a wide range of applications from operational optimization to safety enhancement. Bangert (2021) compiled numerous real-world use cases in this domain, including predictive maintenance and failure prediction for engines, pipeline leak detection, artificial lift problem classification, and multiphase flow rate estimation. Candra et al. (2024) evaluated Support Vector Machine (SVM) and k-Nearest Neighbour (KNN) algorithms for

facies estimation from well log data, finding that KNN produced higher accuracy than SVM. Similarly, Hamzah et al. (2021) also evaluated hydraulically fractured well performance using empirical correlation and machine learning, reporting that machine learning achieved higher prediction accuracy than empirical correlation for production rate and water cut, and could aid in well candidate selection. Zainuri et al. (2023) demonstrated that predicting petrophysical parameters such as porosity and water saturation with machine learning can be prone to issues like overfitting, poor feature selection, and ranking errors, but showed that a workflow integrating ML with petrophysical theory can mitigate these traps and yield accurate predictions even from limited well data. Wardhana et al. (2021) applied several machine learning algorithms including ANN, KNN, Support Vector Regression (SVR), Decision Tree, and Random Forest (RF) to predict Total Organic Carbon (TOC) values from well log data, finding that RF produced the most accurate predictions for the training well while KNN performed best on an independent test well.

In line with these studies, the application of machine learning for estimating FBHP has also gained traction. Several studies in Table 1 have demonstrated that these techniques can achieve accuracy comparable to, and in some cases exceeding, that of traditional empirical correlations. Many regression algorithms from conventional machine learning methods, such as Linear Regression, RF, KNN, SVM, or Gradient Boosting (GB), to modern algorithms like ANN and Long Short-Term Memory (LSTM), were used and showed positive results in estimating FBHP.

Nevertheless, these studies have often focused on limited datasets, resulting in models that do not fully represent general well-flowing conditions. In addition, many of these studies have relied on simplified well geometries, such as vertical wells or specific trajectory types, making them impractical for complex well trajectories. Accordingly, this study is intended to use a large and diverse set of well-flowing conditions, combined with comprehensive tubing geometry using segmentation. This approach enables the modeling of a wider range of flow scenarios and complex well trajectories.

Table 1. Previous studies of FBHP estimation

No.	Authors	Year	Methods	Data	Main Results	Remarks
1	Spesivtsev, P., et al.	2018	ANN with 2 hidden layers	Numerically simulated dataset representing various well flow conditions with 5 types of trajectories (3,500 samples)	ANN model with two hidden layers achieved NRMSE <5%	Limited to 5 types of well trajectories. Relatively limited data points.
2	Kanin, E.A., et al.	2019	RF, GB, SVM, ANN, Surrogate Modeling, Pipe Segmentation	Lab data from various sources based on previous studies (2,560 data points)	GB is best for liquid holdup calculation, flow regime classification, and pressure gradient calculation with $R^2 = 0.93$, accuracy = 88.1%, and $R^2 = 0.95$	Comprehensive approach, used segmentation, relatively limited data points.
3	Tariq, Z., et al.	2020	ANN with Levenberg-Marquardt training, PSO optimization	Published well data (206 data points)	PSO-ANN achieved $R^2=0.98$, AAPE=2.0%	Limited data points. Vertical well only.
4	Nait Amar, M., & Zeraibi, N.	2020	SVR with RBF kernel optimized by Firefly Algorithm	Algerian oil well data (100 measurement points)	SVR-FFA achieved AARD=2.13%, $R^2=0.9981$	Limited data points from specific wells.
5	Sami, N.A., & Ibrahim, D.S.	2021	RF, KNN, ANN	Field data from Middle Eastern oil wells (206 data points)	ANN achieved 2.5% error, best method	Limited data points from specific field / wells
6	Blessing, O., & Agbons, I. S.	2021	RF, GB	Volve field data (3,522 rows after normalization)	RF achieved 97.80% accuracy	Specific field / well data
7	Rathnayake, S., et al.	2022	XGB, linear regression, mixed effects models	Australian coal seam gas well data (91 wells within 5-19 months)	XGB achieved MAPE=10% for individual wells	Specific field / well data
8	Olamigoke, O., & Onyeali, D. C.	2022	SVR, RF, LSTM	Volve field production data (two wells)	LSTM achieved MAPE <2.9%	Limited data points (only 2 wells).
9	Okoro, E.E., et al.	2023	Genetic Algorithm (GA), Imperialist Competitive Algorithm (ICA)	Norwegian Volvo field data (9,161 data points after filtering)	ICA achieved $R^2=0.9985$ -0.9989	Specific field / well data
10	Nwanwe, C.C., et al.	2023	ANN with 3 hidden layers	Middle Eastern wells (1,001 data points)	ANN with 20-15-15 neurons achieved $R^2=0.903$	Limited data points from specific field / wells
11	Nwanwe, C. C., & Duru, U. I.	2023	ANFIS white-box model	Middle Eastern oil field data (1,001 data points)	ANFIS outperformed mechanistic and other ML models	Limited data points from specific field / wells
12	Agwu, E. O., et al.	2025	multivariate adaptive regression splines (MARS)	Numerically simulated dataset representing various well flow conditions.	FBHP equation is provided with training $R^2=0.942$	Comprehensive approach, limited for vertical well only.

METHODOLOGY

To achieve the objectives, this study was divided into several stages as described in Figure 1. First, the range of values of relevant well parameters affecting FBHP calculation was defined. These parameters were then used in simulations to calculate pressure drops in tubing segments using established flow correlations. After that, the simulation results were used to develop a machine learning model through comprehensive training and testing. Once trained, the best-performing model was integrated into an algorithm capable of estimating FBHP under various well conditions. The estimated FBHP values can then be utilized for effective well performance monitoring.

Data preparation for simulation

This initial phase focused on identifying all input variables that affect FBHP based on VLP. Afterwards, the range of values for each variable was predefined to ensure full coverage of the simulation scenarios. The key input variables considered in this study were inlet pressure, average temperature, tubing size, inclination, tubing segment length, gas–oil ratio (GOR), water cut (WCUT), oil American petroleum institute gravity, gas gravity, and VLP. For each variable, an appropriate range of hypothetical values was defined to represent different operating conditions and production fluid properties. The combinations of these variables determined the total number of simulation cases, and the parameter sets

are summarized in Table 2.

Simulation of pressure drop calculation

Building on the predefined parameter sets, the pressure drops across the tubing were modelled using commercial multiphase flow simulation software. A number of simulation runs were carried out to calculate the pressure drops for all parameter combinations. Each simulation produced two main outputs: the liquid flow rate and the pressure drop. This liquid flow rate was then used as an additional variable, combined with the parameter sets defined earlier. Altogether, the simulations produced 790,409 data points.

Machine learning modeling

Following the numerical simulation stage, the next step focused on developing machine learning models to predict pressure drops. As shown in Figure 2, this process began with careful data preprocessing where several tasks were conducted to ensure the dataset was suitable for the next modeling step. Missing data were handled appropriately, numerical features were normalized, and categorical variables were encoded. For example, the Vertical Flow Correlation, which is categorical, was transformed using One-Hot Encoding and represented as a binary vector. As part of an experimental tuning process, Label Encoding was also tried for this feature to explore an alternative approach that might improve

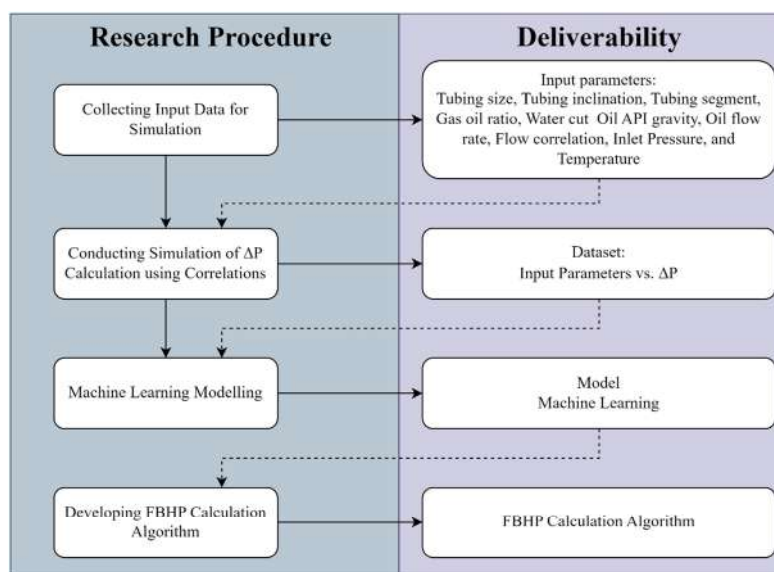


Figure 1. Research procedures

Table 2. Data input for simulation (hypothetical)

Variable	Alias	Unit	Value	Data Format
Inlet pressure	inpress	psia	5000, 2000, 200	numeric
System temperature	temp	°C	30, 75, 150	numeric
Tubing size	diam	in	1, 3.0, 4.5	numeric
Tubing inclination	angle	degrees	0°, 45°, 90°	numeric
Tubing segment length	length	ft	100, 500, 1000	numeric
Gas-oil ratio	gor	scf/stb	100, 1500, 5000	numeric
Water cut	wcut	%	0, 50, 100	numeric
Oil API gravity	api	degrees	20, 35, 45	numeric
Gas gravity	gassg	–	0.6, 0.8, 1.0	numeric
Vertical flow correlation	vlp	–	Duns-Ros (dr), Orkiszewski (or), Beggs- Brill (bb)	text

model performance.

For the numerical features, in addition to VLP and the pressure drop target, normalization was performed using a Standard Scaler, which adjusted values to have a zero mean and a unit standard deviation. This step helped improve performance and stability during model training. A logarithmic transformation was also applied to the Flowrate feature as an experiment to help improve model performance and keep it consistent with other numerical variables. After preprocessing, the dataset was randomly divided into training, validation, and testing sets with proportions of 70%, 15%, and 15% (553,286, 118,562, and 118,561 data points). This split ensured a fair model evaluation and helped prevent data leakage between subsets.

After the preprocessing phase, the training of the machine learning model was carried out, during which the model parameters were optimized using the training dataset. Following this training, the model was validated using a validation dataset to assess its generalization capability. Once these steps were complete, the model was then evaluated by comparing the estimated values with those calculated from the flow correlations using the testing dataset.

Standard regression performance metrics were used to assess model accuracy. The evaluation focused on comparing the correlation-derived pressure drop versus the predicted pressure drop, using metrics such as MAE, MAPE and R^2 . Other metrics, including MSE and RMSE, were not used as the primary basis for evaluation because their values

could vary depending on the pressure drop range. If the error remained high, hyperparameter tuning and experiments were carried out and the training was repeated until the best-performing model was achieved.

ANN model experiments

A series of experiments were carried out to examine how different configurations affected the model performance. These experiments covered not only the parameter tuning, but also model architecture and data preprocessing techniques.

The architecture experiments tested several layer configurations to find the balance between model complexity and generalization. Four different setups were evaluated based on the basic architecture as shown in Figure 3. The first configuration used an input layer connected to layers with 64, 32, and 16 nodes before the output. The second configuration expanded the structure by using 128, 64, 32, and 16 nodes. The third tested configuration included 256, 128, 64, 32, and 16 nodes. Finally, the last configuration used a model of 512, 256, 128, 64, 32, and 16 nodes.

In addition to architecture, various activation functions such as ReLU, ELU, LeakyReLU, and SoftPlus were also tested. Regularization methods including BatchNorm1d and Dropout were also applied to improve training stability and help prevent overfitting. Batch sizes ranging from 64 to 8,192 were also evaluated to understand their effect on training convergence. The number of training epochs also varied between 50 and 2,000 depending on model complexity and the stability of the results.

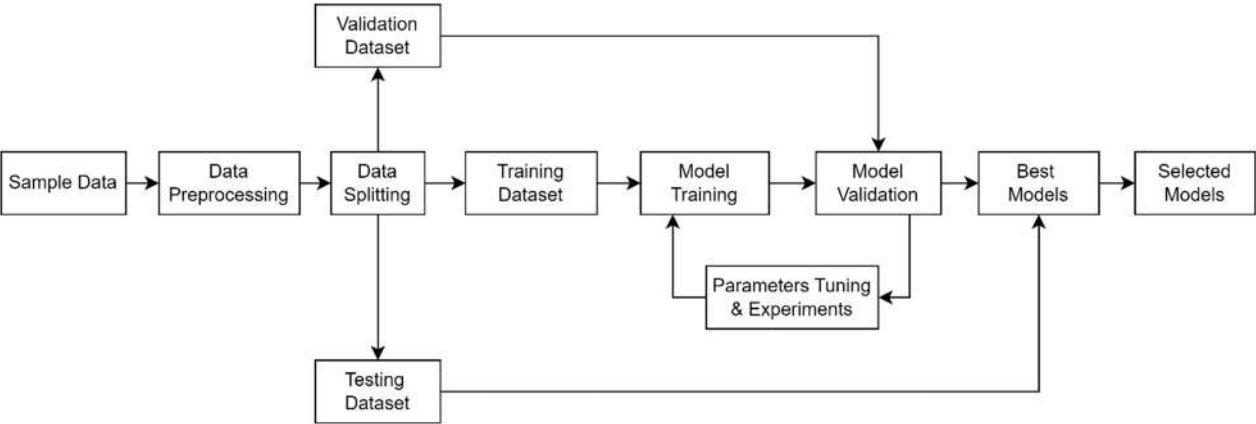


Figure 2. Machine learning modeling procedure

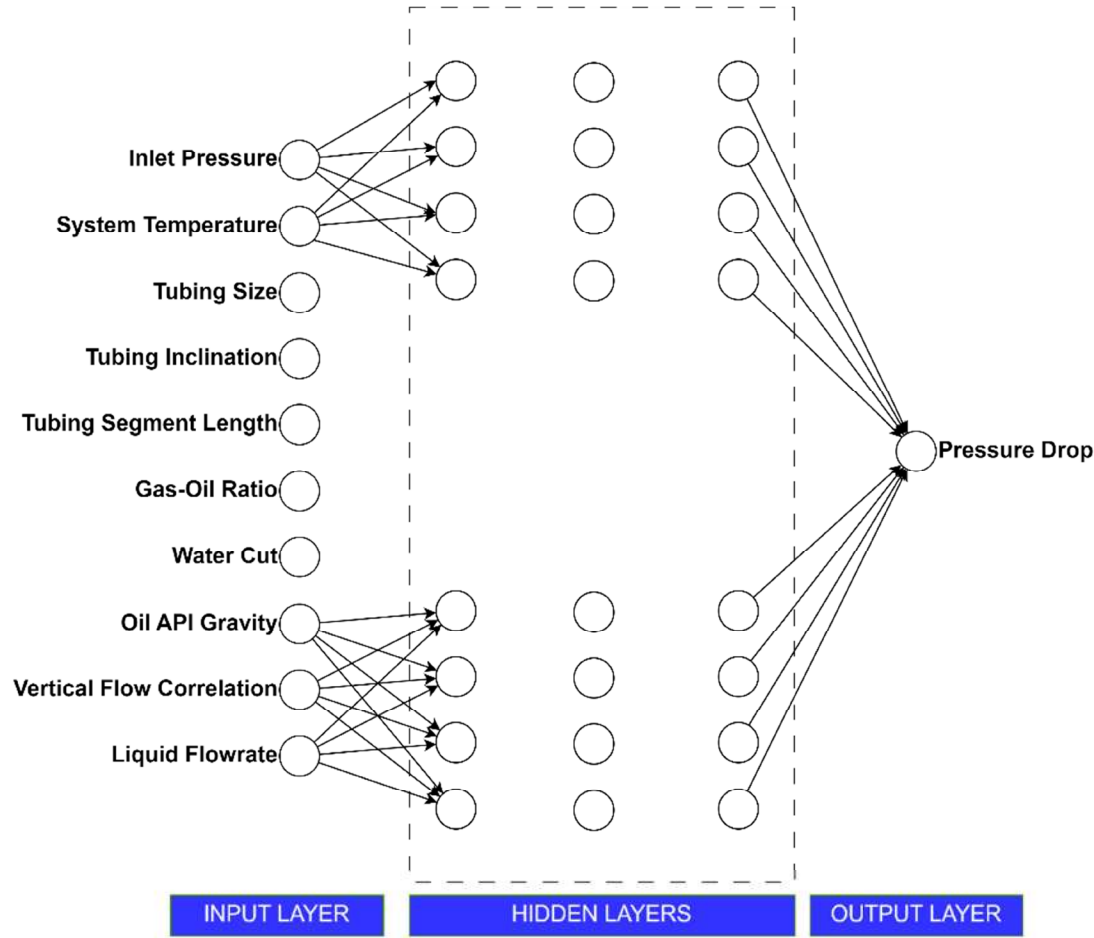


Figure 3. ANN model architecture

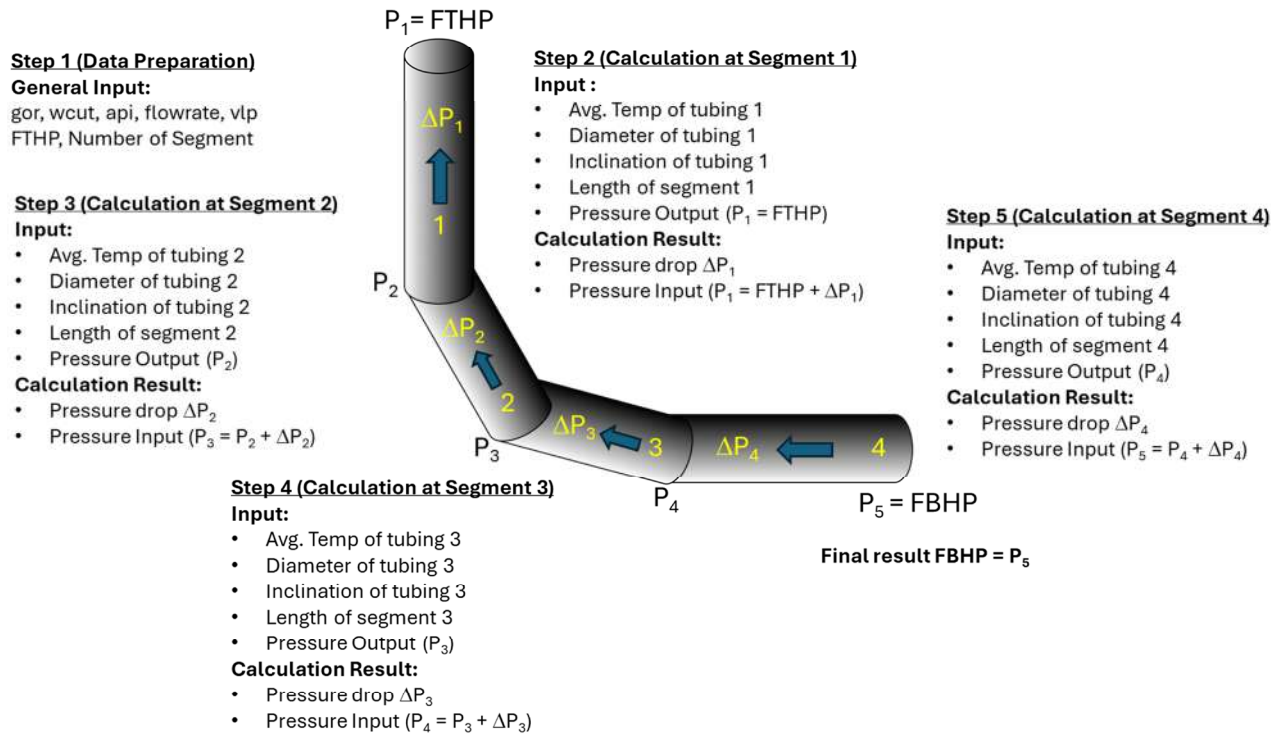


Figure 4. FBHP calculation logic

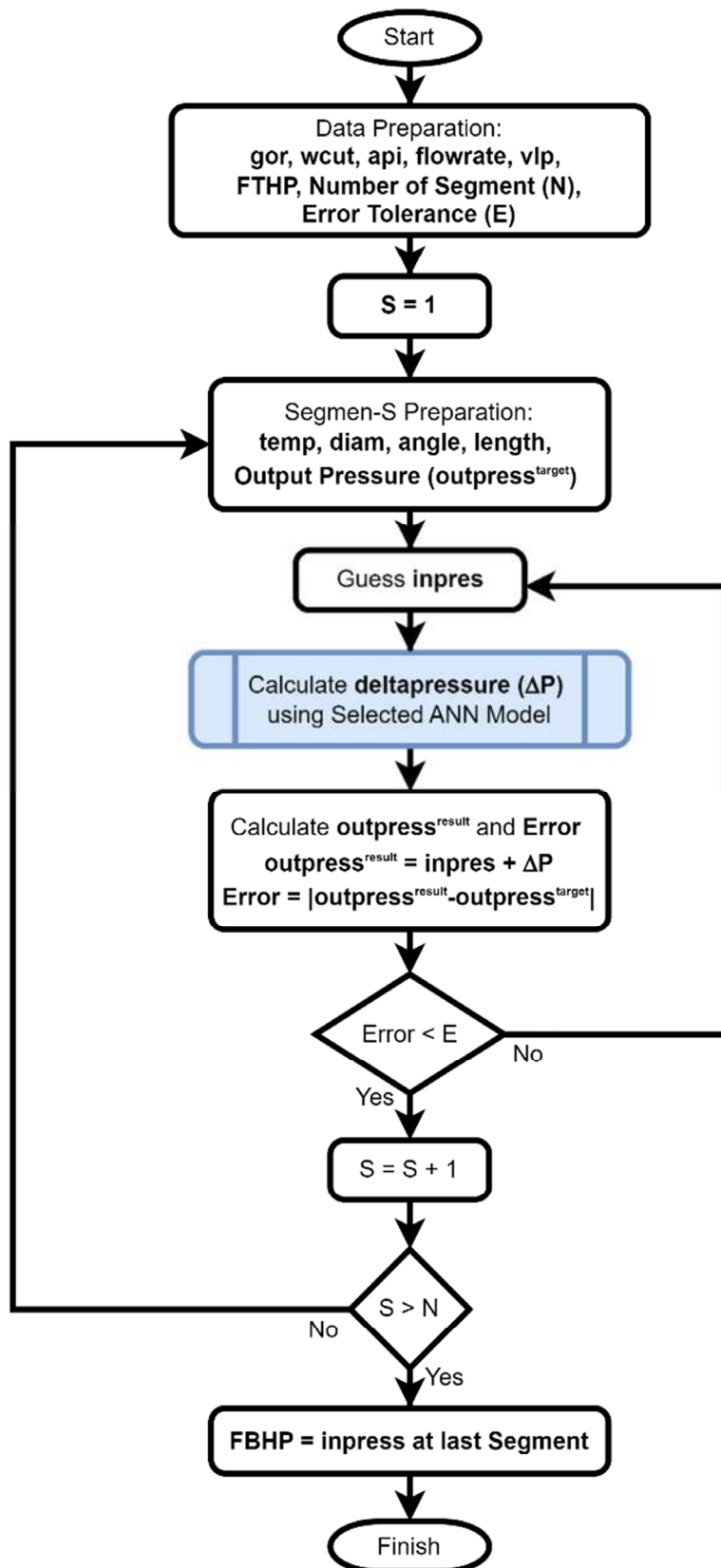


Figure 5. FBHP calculation algorithm

From the data view, the experiments also compared model performance using the full dataset versus the models trained limited to flow rates below 10,000 STB/d to assess whether removing extreme values could help reduce bias. The effect of using raw Flowrate values versus logarithmic Flowrate values was also tested to see if transforming skewed data would give more accurate results. Finally, the VLP feature was processed using both Label Encoding and One-Hot Encoding to compare their impact on the model's predictive capability.

FBHP calculation algorithm

The best ANN model obtained from the modeling step was then used to estimate FBHP for any new datasets. This estimation process was relatively straightforward and fast, but had to be carried out step by step for each tubing segment. As described in Figure 4, the process began by preparing the required input data, starting with the uppermost tubing segment closest to the wellhead. The required input included temp, gor, wcut, American petroleum institute, flowrate, vlp, number of segments, diam, angle, length, and output pressure, with the output pressure for the first segment set equal to the Flowing Tubing Head Pressure (FTHP). Once the input data were prepared, the pressure drop of each segment was calculated using the selected ANN model. The FBHP was then determined by summing the pressure drops across all the tubing segments. It should be noted, however, that because the known pressure parameter of each segment corresponds to its output,

an iterative looping process is required to ensure that the calculated output pressure closely matches the known pressure. This looping can be performed using the Newton–Raphson method. Detailed FBHP calculation procedure for the whole well trajectory is shown in Figure 5.

RESULT & DISCUSSION

Table 3 presents the statistical summary of the numerical simulation results used for model development. The dataset contains huge data points, with flowrates ranging widely from as low as 0.084 STB/d to a maximum of 19,999.1 STB/d. The resulting delta pressure values ranged from 0.016 psia to 4,952.4 psia, with an average of about 485.34 psia. Table 4 presents random samples of this simulation results. After the data preprocessing, those datasets were transformed into different scales and formats as shown in Table 5.

After extensive experiments of different model structures and parameters, the best ANN architecture obtained was a model with six hidden layers arranged with 512, 256, 128, 64, 32, and 16 neurons before the single output layer. Each layer was followed by a ReLU activation function, and the network output used a SoftPlus activation to ensure positive outputs and smoother curves than standard ReLU. The model was trained using the L1 Loss function (mean absolute error) with the AdamW optimizer, a learning rate of 0.001, and a weight decay of 0.0001

Table 3. Numerical simulation result statistics

	in press	temp	flowrate	api	gassg	wcut	gor	diam	length	angle	delta pressure
count	790k	790k	790k	790k	790k	790k	790k	790k	790k	790k	790k
mean	1900.9	84.13	4053.6	33.03	0.8	46.91	2294.9	2.39	303.8	46.43	485.34
std	1930.6	49.17	4720.7	10.24	0.16	40.28	2076.6	1.44	199.9	36.46	954.98
min	200	30	0.084	20	0.6	0	100	1	100	0	0.016
25%	200	30	515.53	20	0.6	0	100	1	100	0	49.11
50%	2000	75	2097.87	35	0.8	50	1500	3	500	45	136.8
75%	2000	150	5957.7	45	1	100	5000	3	500	90	281.8
max	5000	150	19999.1	45	1	100	5000	4.5	500	90	4952.4

Table 4. Numerical simulation result samples

inpress	temp	api	gassg	wcut	gor	diam	length	angle	log flowrat	vlp	delta pressu re
200	75	35	0.8	50	100	4.5	100	45	8.63	or	73.0
200	75	45	1.0	50	100	4.5	500	45	6.92	dr	112.4
5000	150	35	1.0	0	5000	1.0	500	45	7.66	dr	4067.5
5000	150	35	0.8	100	100	1.0	500	90	8.57	bb	3536.5
200	30	20	0.6	50	100	4.5	500	90	7.52	bb	24.0
2000	150	35	1.0	100	1500	1.0	100	90	9.05	dr	1920.3
5000	150	35	1.0	50	100	1.0	100	0	7.73	or	199.8
200	150	35	1.0	0	1500	1.0	100	0	0.81	or	15.0
200	150	45	0.6	100	5000	3.0	100	90	9.51	dr	151.0
200	150	45	0.6	100	100	4.5	100	0	8.83	dr	109.7

Table 5. Transformed simulation result samples

X0	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
-0.881	-0.185	0.1919	0.0004	0.0766	-1.057	1.4592	-1.019	-0.039	0.7371	0	0	1
-0.881	-0.185	1.168	1.2253	0.0766	-1.057	1.4592	0.9812	-0.039	-0.200	0	1	0
1.605	1.339	0.191	1.2253	-1.164	1.3027	-0.970	0.9812	-0.039	0.2052	0	1	0
1.605	1.339	0.191	0.0004	1.3179	-1.057	-0.970	0.9812	1.1948	0.7052	1	0	0
-0.881	-1.100	-1.272	-1.224	0.0766	-1.057	1.4592	0.9812	1.1948	0.1302	1	0	0
0.051	1.339	0.191	1.2253	1.3179	-0.382	-0.970	-1.019	1.1948	0.9701	0	1	0
1.605	1.339	0.191	1.2253	0.0766	-1.057	-0.970	-1.019	-1.273	0.2444	0	0	1
-0.881	1.339	0.191	1.2253	-1.164	-0.382	-0.970	-1.019	-1.273	-3.556	0	0	1
-0.881	1.339	1.168	-1.224	1.3179	1.3027	0.4179	-1.019	1.1948	1.2243	0	1	0
-0.881	1.3393	1.1681	-1.224	1.3179	-1.057	1.4592	-1.019	-1.273	0.8494	0	1	0

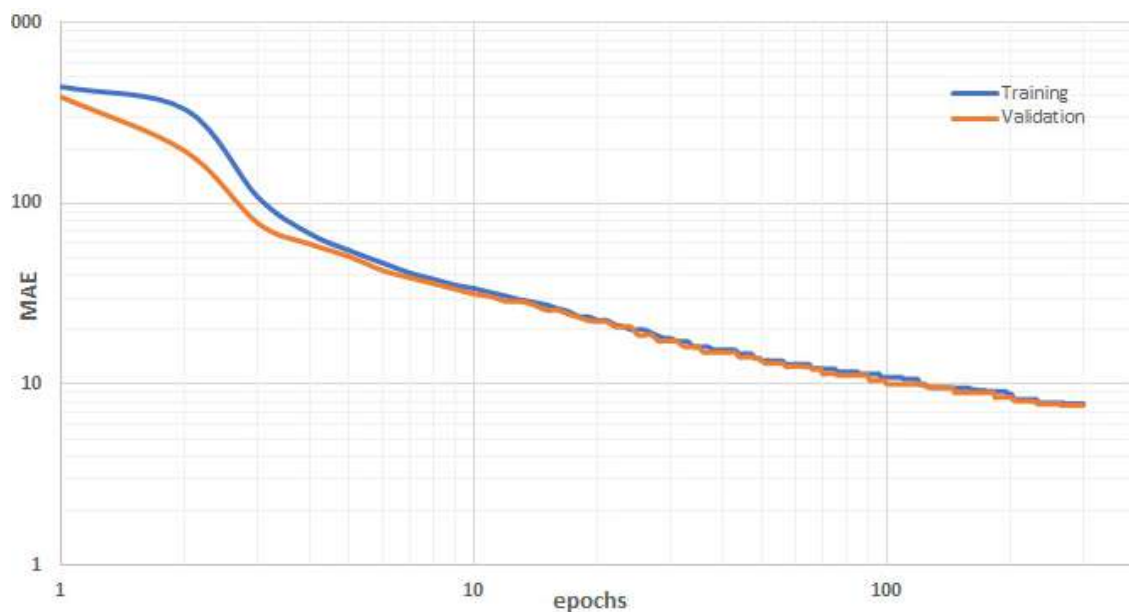


Figure 6. Mean absolute error trend on training & validation

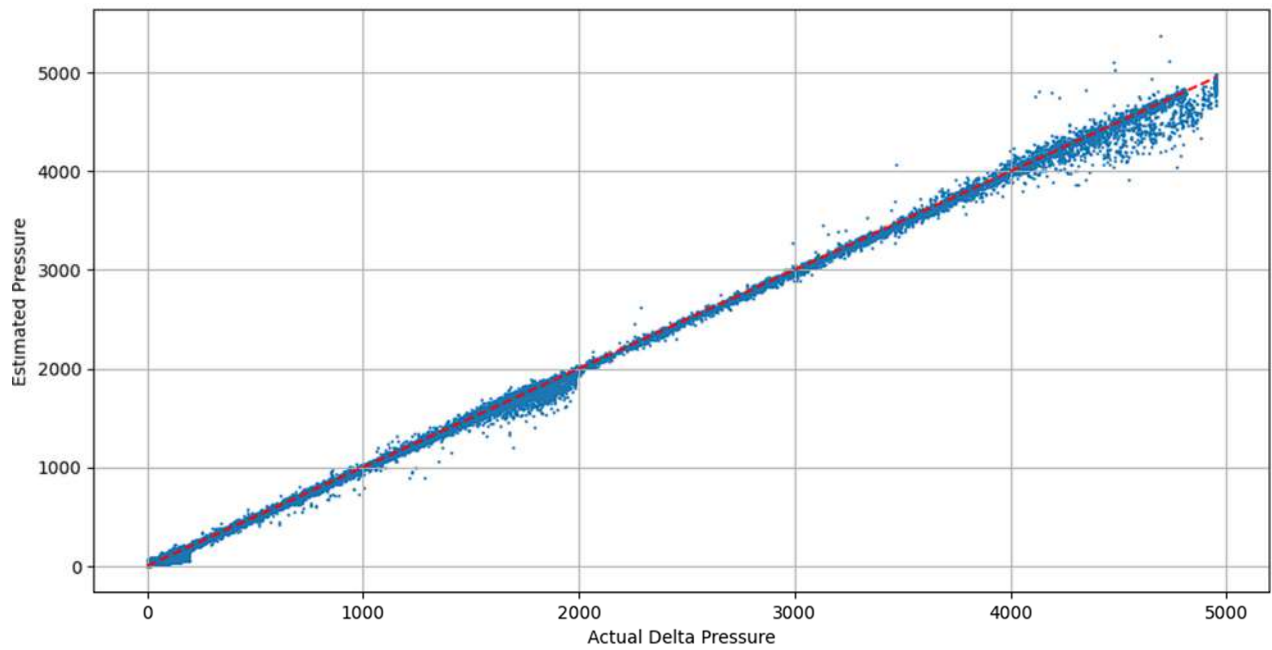


Figure 7. Pressure drop prediction (simulation vs model) on testing dataset

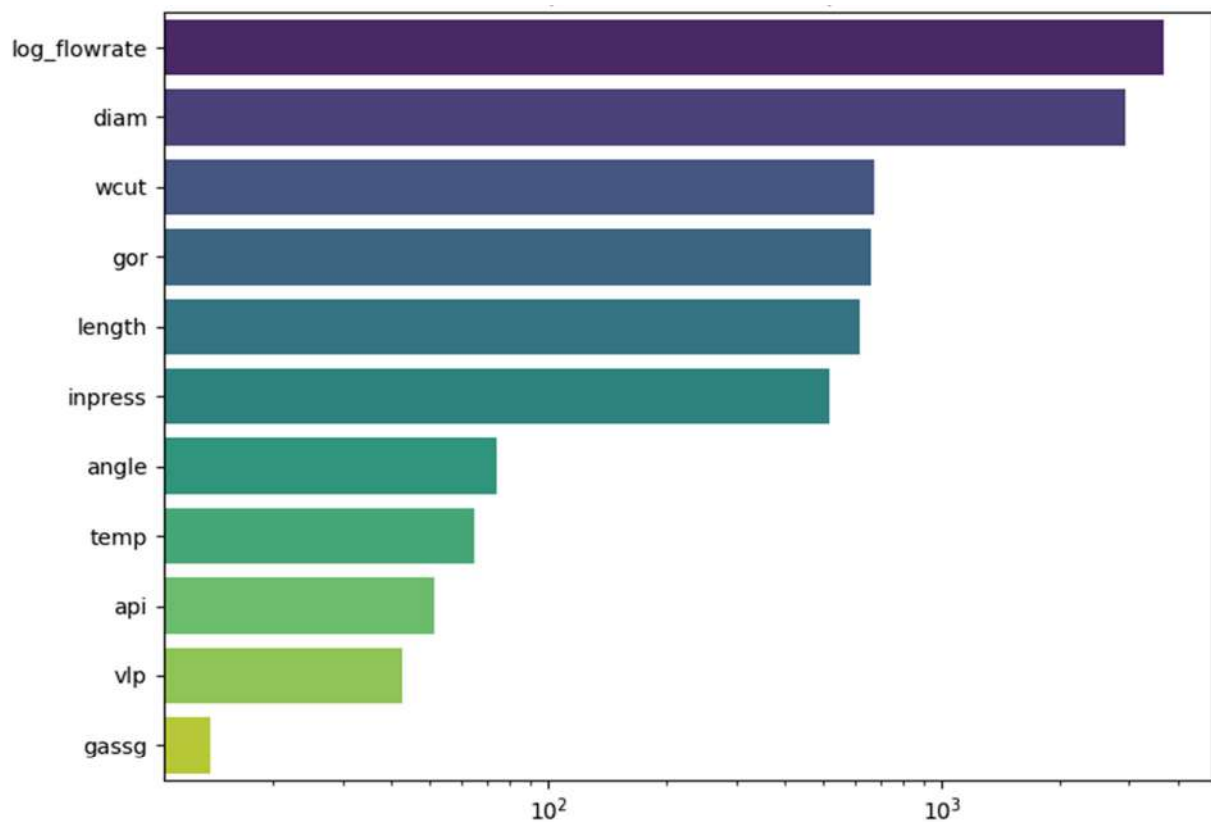


Figure 8. Model feature importance

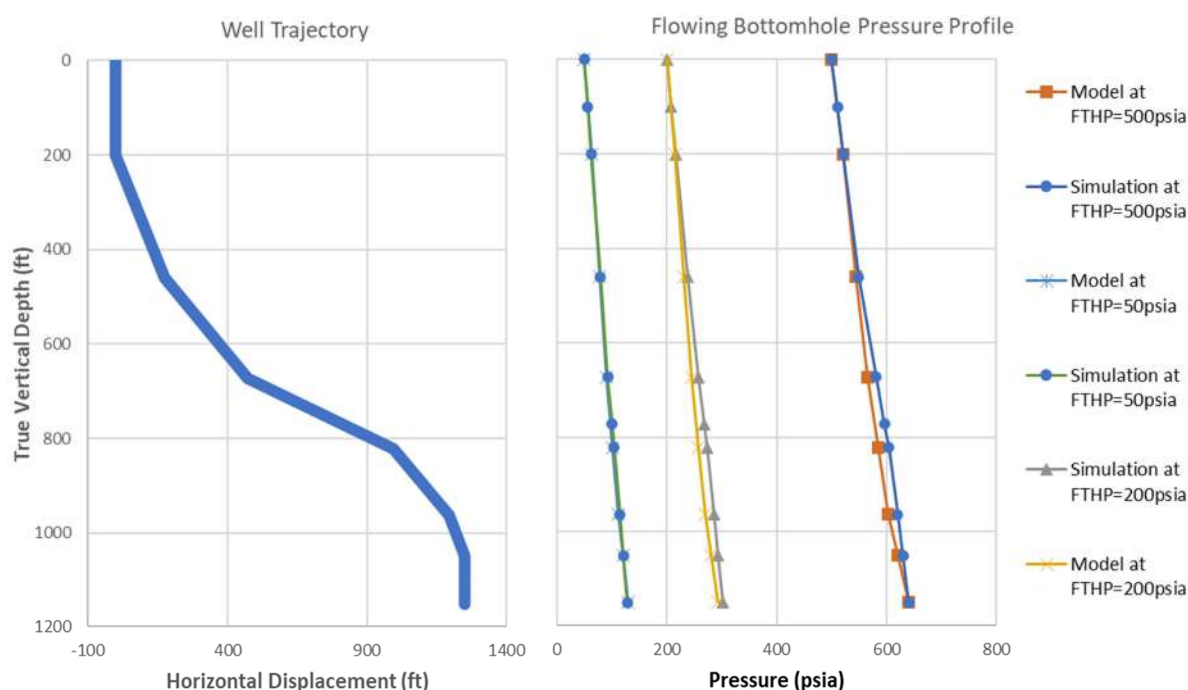


Figure 9. FBHP result comparison

for regularization. Training was conducted for 300 maximum epochs with a batch size of 8,192. The best results were achieved using One-Hot Encoding for the VLP feature and the logarithmic transformation of the Flowrate feature, which reduced the data skewness.

As shown in Figure 6, the training & validation MAE were initially very high (446.1 and 387.8 psia), indicating that the model had not yet recognized data patterns. Over time, the model gradually improved its predictions, achieving its best performance at epoch 296 with training and validation MAE of 8.37 and 7.69 psia. This significant reduction demonstrated that the model successfully generalized the data and made accurate pressure predictions relative to the scale of the pressure drops data.

This best model was then tested on the testing dataset and the comparison plot between simulated pressure drops versus predicted pressure drops of this testing dataset is shown in Figure 7. The plot shows an R^2 value of 0.9993 and testing MAE of 7.8259 psia. This demonstrates that the model performs excellent on predicting the pressure drops of all the variations of data.

In addition to that performance metrics evaluation, the influence of each input variable on the model's performance was also ranked. This feature importance analysis was carried out using the permutation of the feature importance method from the scikit-learn library by randomly shuffling the values of each variable in turn, then measuring the decrease in the model's accuracy caused by this change. Figure 8 concludes that the variables with the greatest impact on the model were log flowrate, tubing diameter, water cut, gas-oil ratio, segment length, and inlet pressure. Other variables like tubing inclination, temperature, American petroleum institute gravity, type of VLP, and gas specific gravity, although not as dominant, still influenced the model, enabling it to achieve high accuracy.

Figure 9 compares the FBHP results from the developed model with those from the numerical simulation. The analysis was conducted at a temperature of 75 °C, flow rate of 500 STB/day, American petroleum institute gravity of 45, gas specific gravity of 0.8, water cut of 50%, gas-oil ratio of 3,000 SCF/STB, and tubing diameter of 3.0 inches, using the Beggs-Brill correlation, with the detailed well trajectory also shown in the chart. At FTHP

GLOSSARY OF TERMS

Symbol	Definition	Unit
ANN	Artificial Neural Network	-
API	American Petroleum Institute (in API Gravity)	°API
DIAM	Tubing Diameter	in
ELU	Exponential Linear Unit (activation function)	-
FBHP	Flowing Bottomhole Pressure	psia
FTHP	Flowing Tubing Head Pressure	psia
GOR	Gas–Oil Ratio	SCF/STB
KNN	k-Nearest Neighbour (machine learning algorithm)	-
LSTM	Long Short-Term Memory (type of recurrent neural network)	-
MAE	Mean Absolute Error	psia
MAPE	Mean Absolute Percentage Error	%
NRMSE	Normalized Root Mean Square Error	fraction
PSO-ANN	Particle Swarm Optimization - Artificial Neural Network	-
R ²	Coefficient of Determination	-
RF	Random Forest (machine learning algorithm)	-
ReLU	Rectified Linear Unit	-
SCF	Standard Cubic Feet	-
STB	Stock Tank Barrel	-
SVM	Support Vector Machine	-
SVR	Support Vector Regression	-
VLP	Vertical Lift Performance	-
WCUT	Water Cut	%

values of 50, 200, and 500 psia, the developed model predicted FBHP values of 129.8, 293.0, and 640.2 psia, while the numerical simulation produced 127.8, 302.3, and 640.6 psia. The corresponding absolute

percentage errors were 1.54%, 3.07%, and 0.06%, respectively. These results demonstrated that the model closely reproduced the simulation outcomes, with acceptable deviations. Moreover, from the pressure trends along the wellbore from wellhead to bottomhole, the pressure profiles generated by both methods nearly coincided, indicating a strong consistency between the model and the simulation.

CONCLUSION

The results of this study indicated that the developed machine learning model could estimate pressure drops and predict FBHP with a high degree of accuracy across the simulated well conditions. The model achieved very small errors and an R² value for testing dataset of 0.9993, suggesting strong capability in capturing the relationships between input variables and FBHP. However, it should be emphasized that these results were obtained primarily from numerically generated datasets, which, while extensive and diverse, may not capture the full variability of real field data. Therefore, although the model showed strong potential for application in well performance monitoring, further testing with field-scale datasets and practical deployment scenarios is necessary to confirm its reliability and scalability in real-world operations. To extend this study further, future research could expand the scope of pressure drop calculations to include gas wells, which would broaden the production scenarios. Deployment could also be scaled beyond individual wells to entire production networks, enabling comprehensive system-wide not only well's FBHP but also pressure profile in production networks. Additionally, integrating more vertical flow correlations and more machine learning algorithms could also improve prediction accuracy by making better representation of various conditions.

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