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Application of artificial intelligence in predicting the dynamics of bottom hole pressure for under-balanced drilling: Extra tree compared with feed forward neural network model

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ABSTRACT

This study used six fields data alongside correlation heat map to evaluate the field parameters that affect the accuracy of bottom hole pressure (BHP) estimation. The six oil field data were acquired using measurement while drilling device to collect surface measurements of the downhole pressure data while drilling. For the two case studies, measured field data of the wellbore filled with gasified mud system was utilized, and the wellbores were drilled using rotary jointed drill strings. Extremely Randomized Tree and feed forward neural network algorithms were used to develop models that can predict with high accuracy, BHP from measured field data. For modeling purpose, an extensive data from six fields was used, and the proposed model was further validated with two data from two new fields. The gathered data encompasses a variety of well data, general information/data, depths, hole size, and depths. The developed model was compared with data obtained from two new fields based on its capability, stability and accuracy. The result and model's performance from the error analysis revealed that the two proposed Extra Tree and Feed Forward models replicate the bottom hole pressure data with R^2 greater than 0.9. The high values of R^2 for the two models suggest the relative reliability of the modelling techniques. The magnitudes of mean squared error and mean absolute percentage error for the predicted BHPs from both models range from 0.33 to 0.34 and 2.02%–2.14%, for the Extra tree model and 0.40–0.41 and 3.90%–3.99% for Feed Forward model respectively; the least errors were recorded for the Extra Tree model. Also, the mean absolute error of the Extra Tree model for both fields (9.13–10.39 psi) are lower than that of the Feed Forward model (10.98–11 psi), thus showing the higher precision of the Extra Tree model relative to the Feed Forward model. Literature has shown that underbalanced operation does not guarantee the improvement of horizontal well's extension ability, because it mainly depends on the relationship between the bottomhole pressure and its corresponding critical point. Thus, the application of this study proposed models for predicting bottomhole pressure trends.

1. Introduction

Under-balanced drilling (UBD) is the practice of drilling a well with the wellbore fluid gradient less than the natural formation gradient. It differs from conventional drilling in that the bottom hole circulating pressure is lower than the formation pressure, thereby permitting flow of fluid within the well while drilling proceeds [1]. Besides minimizing lost circulation at increased bit penetration rate, this technique has a widely recognized benefit of

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minimizing the damage caused by invasion of drilling fluid into the formation [2]. In many UBD applications, additional benefits include reduction in drilling time, increase in bit life, and early detection and dynamic testing of productive intervals while drilling [3]. Because the majority of hydrocarbons today are found in existing fields with depleting pressures, or in complex and low quality reservoirs, then UBD presents itself as an economically laudable option. UBD has proven to be an economical method for drilling in depleted/low pressure reservoirs. Since it is possible to document production data during drilling, operators can easily and accurately identify inflow mechanisms and pay intervals, and cease drilling operation as soon as the target zones are identified [4]. Bottom hole pressure (BHP) cannot be directly controlled in actual operation, but can be changed by regulating the wellhead pressure [5,6]. BHP is controlled by opening or closing the choke to lower or raise the standpipe pressure. This technique essentially creates an increasing fluid density gradient between the surface and the bottom hole.

Experience has shown that proper design of a UBD program can provide significant technical and economic benefits, such as reduced formation damage, increased drilling penetration rate, and improved recovery under the right conditions [7]. It is true that maintenance of bottom hole pressure (BHP) underscores the success of UBD [8]. Flow through annulus is an ambiguous area of research for evaluating flow parameters, especially BHP. In this way, intelligently smart technologies can solve this ambiguous problem in the design of UBD hydraulic components, which are largely dependent on BHP [9,10]. An effective design strategy of a well using UBD technique depends on the accurate prediction of its BHP which may be calculated or determined through several methods. According to Amar et al. [11], "it is not often practical or economical to use well test or deploy a permanent pressure gauge downhole as a simple strategy for predicting BHP". Also, most of the mechanistic models and correlations proposed in literature are limited to some conditions and intervals of application [12–14]. Ahmadi et al. [15] also highlighted the inability of the developed mechanistic and conventional models or correlations to estimate BHP within low uncertainties and high accuracies. Underbalanced drilling has been used in drilling as it has conspicuous technical superiorities compared to overbalanced drilling, and the influx behavior of reservoir fluids depends on the pressure difference between the reservoir pore pressure and the bottom hole pressure [4]. Thus, in order to establish a timely and accurate model that ensures a large coverage of real time subsurface conditions with reduced cost as a means of predicting BHP, it is vital to incorporate some basic components in a sufficiently robust and well-thought out smart UBD program.

Yaghini et al. [16] highlighted that the inaccuracies caused by default training algorithms often trapped in local minima are the key challenges encountered when using artificial neural network (ANN) models, but with sufficient field data sets, the neural network can be trained to predict pressure values much closer to the measured values than those of most existing models. Sensitivity analysis (SA) is a key step that involves the assessment and propagation of uncertainties.

Complex environmental models typically require global sensitivity analysis (GSA) to account for non-linearity and parametric interactions [17]. Decision tree-based methods have been investigated with relatively small sample size for non-linear regression or classification problems, and they are also able to handle both numerical and categorical inputs [18,19]. These methods rely on ensembles of decision trees which match partitions of the input space with a predicted output, and are commonly implemented using the random forests and Extra-Tree algorithms [20]. The variable important metrics provided by the tree-based methods can be assessed in relation to the criteria summarized by Pianosi and Wagener [21] for an "ideal" sensitivity metric. Because, the multiple document interface (MDI) and multiple discriminant analysis (MDA) metrics largely meet the criteria of being suitable for global sampling designs, independent of model structure, relatively easy to implement numerically, and stable across sample sizes. Feed forward neural network was also considered because, the optimization of weights in multilayer perceptron models amounts to an iterative search for an acceptable minimum. The optimization of the network weights is performed using iterative, nonlinear mathematical optimization methods from literature [22,23]. Multilayer perceptron networks are general classifiers, in which the form of the class probability distribution functions is not assumed.

With the right design and use, UBD method may eliminate formation damage and minimize overall drilling cost by: increasing rate of penetration, extending bit life, drilling formation with small drilling windows, avoiding fluid loss, reducing drilling time and most importantly, increasing well productivity and safety during drilling operations. In the oil and gas industry, deep wells are drilled to reach hydrocarbon deposits (reservoir). The depth of the wells can reach several thousand meters or more. At this depth, the well formation and pressure can reach several hundred bars (or psi). Some wells use downhole sensors to record data. Because installing sensors is a costly process, and these data are not available in real time for a large number of wells. During underbalanced drilling the bottomhole pressure is kept below the formation pore pressure. However, knowledge of these parameters is essential for effective and safe control of the well start after completion and production. Determining downhole parameters is a difficult and important task. This article suggests using a machine learning approach and develop a neural network model that can be trained with available field data, and the model is then used to predict the bottomhole pressure trends [24].

Maintaining subsurface conditions from beginning to the end of the drilling process is necessary to guarantee a successful UBD operation. However, maintaining the UBD operations requires an accurate prediction of BHP. This study used bottom hole pressure data measured while drilling from six fields to first evaluate the field parameters that affect BHP prediction accuracy using correlation heat-map, and this will help avoid the undesired errors from the predictive model. Thus, Extremely Randomized Tree (extra tree) algorithm which is a decision tree based method and feed forward multilayer perceptron networks were adopted for this study. Decision trees are a simple and well-established general approach for statistical learning; such trees aim to identify the splitting criteria which describes the relationship between a set of input combinations, and regions of the output space. The strength of the multilayer perceptron networks lies in the fact that are theoretically capable of fitting a wide range of smooth, nonlinear functions with very high levels of accuracy. The two machine learning approaches can systematically assess the range of field measured parameters and make an accurate prediction with the sufficient field data sets available in this study. The study on estimation of BHP still needs attention because to ensure safe and stable drilling operation, BHP should be maintained.

2. Methodology

Predictive modeling is the process of creating, testing and validating a model to best predict the probability of an outcome. Each model has its own strengths and weaknesses and is often best suited for specific problems. These models were created by developing an algorithm using measured field data and saving the model for reuse, in order to analyze results without the measured data, by using trained data alongside the developed algorithm. This study developed two predictive models using extra tree and feed forward neural network, and the choice of these two was to avoid some predominant challenges that suffice in the application of artificial neural network, which includes difficulty of convergence attributed to poor initial guess, convergence at the local minimum vis-a-viz poor estimations or predictions.

2.1. Wellbore bottom hole pressure estimation

This is the pressure usually measured in pounds per square inch at the bottom of the hole in a drilled well. This pressure may be calculated in a static, fluid-filled wellbore using equation (1).

$$BHP = MW * Depth * 0.052 \quad (1)$$

Where, BHP is the bottom hole pressure in pounds per square inch, MW is the mud weight in pounds per gallon, Depth is the true vertical depth in feet, and 0.052 is a conversion factor if these units of measurements apply. For circulating wellbores, the BHP increases by the amount of fluid friction in the annulus [25].

This estimation is different from well testing, because in well testing operations, pressure is measured in a well at or near the depth of the production zone. The well bottom hole pressure depends on several factors. The composition of the drilling fluid in circulation and how it influences the hydrostatic pressure in the well, while considering the relationship between the friction pressure loss in the well and the fluid velocity and fluid composition.

Several researchers have proposed methods for predicting and estimating bottom hole pressure using neural networks and correlations with emphasis on complex two phase flow through an annulus [26]. Li et al. [4] in their study improved on the existing study on BHP estimation by considering the density behavior of the drilling fluid system and wellbore heat transfer. But, most of these studies did not utilize real time data which often show fluctuations in the bottom hole pressure in their estimations. If these BHP fluctuations are not properly captured during prediction, the pressure will no longer be maintained below the formation pressure and the formation will then be in an overbalanced state. The duration of these overbalance can destroy or reduce the benefits that come from the effort and expense to drill the underbalanced well [27].

The use of different drilling systems, such as snubbing and coiled tubing units, have been attempted as potential solutions to achieve 100% underbalanced conditions; however, their successes have been limited to specific conditions [28–30]. A solution to ensure that wells are maintained in underbalanced drilling is to reduce the target bottom hole pressure low enough to accommodate any pressure fluctuation that may occur. Therefore, a preferable approach is to fully understand the dynamics of flow behavior during UBD operations and use this information to more effectively control the bottom hole pressure.

The necessity of maintaining 100% underbalanced conditions and controlling BHP fluctuation within a desirable UBD pressure window serves as motivation for this study. Therefore, its main focus is to improve bottom hole pressure control for UBD operations so as to maintain apt underbalanced conditions and avoid formation damage.

2.2. Extremely Randomized Tree background

Extra tree is a tree-based ensemble method for supervised classification and regression problems [31,32]. The objective of adopting randomized tree in the context of the numerical input features, is that the optimal cut-point is responsible for a large proportion of the variance of the induced tree. This idea is rather productive in the context of many problems characterized by a large number of numerical features varying more or less continuously: it often leads to increased accuracy due to its smoothing and significant reduction in computational burdens linked to determination of optimal cut-points in standard trees. In the extreme case, it builds totally randomized trees whose structures are independent of the output values of the learning sample. The strength of the randomization can be tuned to problem specifics by the appropriate choice of a parameter [33].

The Extra Tree-algorithm follows the classic top-down procedure to create a series of raw gradient or regression trees. The two main differences between extra tree and other tree-based clustering methods are that it separates nodes by selecting cut-points at random and grows the tree using the entire learning sample. Tree forecasts are combined to produce the final prediction, by majority vote in classification problems and arithmetic average in regression problems. According to John et al. [34], “extra tree employs random subset features to train each base estimator”.

In terms of bias-variance, the logic behind the Extra Tree method is that the explicit randomization of the cut-points and attribute combined with ensemble averaging can reduce contrasts/similarities more than the weaker randomization schemes used by other methods. From a computational point of view, the complexity of the tree growing procedure, assuming balanced tree, lies in the $N \log N$ scheme with respect to learning sample size. The Extra tree approach consists of two factors, K and M. K represents the number of variables unsystematically selected at each node n_{min}, which represents the smallest sample size that separates a particular node. Constraints K, n_{min}, and M (M is the number of trees in the ensemble model) create different impacts; K determines the power of the unique selection procedure, n_{min} determines the power of the aggregating yield sound, and M determines the power of alteration decrease of the collaborative archetypal accumulation [33]. Seyyedattar et al. [35] highlighted the details on the Tree-based structure where they explained the importance of the root, internal and leaf nodes.

The extra tree adopted in this study works by recursive partitioning of the input data set using randomly generated splits of smaller subsets based on a defined cut-point (threshold), to create the BHP prediction model that is capable of forecasting the fluctuations from the set of measured field data used as input parameters.

2.3. Feed forward neural network

Singh and Saraswat [36] noted that, “Feed forward neural network architecture is widely used for generalized pattern classification and pattern mapping task”. In recent years, the use of feed forward neural networks has grown significantly in solving modeling problems. The advantage of using feed forward neural networks directly for classifying and modeling data is the flexibility of a distributed model defined by network weights. Linear and non-linear resolutions can be determined by properly configuring the neural network. Adding a hidden layer with the appropriate transfer function converts a simple two-layer linear neural network (input and output) into a three-layer network capable of general modeling [37].

Feed forward neural networks can be considered as widely used mathematical tools to study the relationship between independent variables acting as input to the network and dependent variables specified as output to the network [38]. Learning occurs when a series of “trained” data with well-known identities and linear spectra are added to the network and the weight of the network is changed to reduce the difference between the network output (predicted or estimated data) and actual data or output. Therefore, the network is trained so that the relationships between the input and output variables are encoded in the network model [39]. After the weights are adjusted using the samples in the training data, the network can be used to predict the same class of data.

2.4. Development of the BHP predictive model

The purpose of this study is to develop a smart model to forecast the bottom hole pressure for proper underbalance drilling management, based on real time field data. The interdependence of design criteria makes the process of modeling with artificial neural networks more complex compared to traditionally supervised pattern recognition techniques. The modelling techniques used in this work are Extra Tree and feed forward neural network. The performance and accuracies of the models have been assessed using error analyses.

In this study, depth, temperature and pressure gradient were used as the independent input variables (X), while the BHP to be estimated is the dependent variable (Y). This was used in the development of the BHP models using Extremely Randomized Trees (Extra Trees) and feed forward neural network algorithm. In the data sheet, the data was inputted as X0, X1, X2, Y which represent depth, T, PG and BHP respectively. The splitting of the data for training and testing was done using the random train, test and split with the random number indices generator also known as random states, set to a value of 5, and a training to testing ratio of 8:2 was adopted.

2.4.1. Extra Tree Modeling

Hyper parameters are tunable parameters that allow any algorithm to give an optimum performance in terms of accuracy, speed, and efficiency. To achieve these, two hyper sensitive parameters were tuned in the course of this study and the others were left to perform at their default states. The random state was set to 65 while the optimum number of trees was set to 6. With the random state set to 6, a sub-optimal greedy algorithm is called to repeat 6 times with features and samples selected randomly, the aggregate of these random sampling helps to control uniformity of result, provided the values remain unchanged. The number of decision trees is used to control the stability of performance, although ensemble algorithms like Extra Trees are known to be somewhat immune to overfitting of the training data set, therefore increment in number of decision trees will most unlikely lead to overfitting and however, accuracy and efficiency of the algorithm is controlled at their best. The codes are attached as Appendix A.

2.4.2. Feed forward neural network modeling

In this study, depth (ft), temperature (°F) and pressure gradient (psi/ft) were used as the independent input variables for the prediction of the bottom hole pressure (BHP) by a Feed Forward Neural Network. The data sample was fed into the model in the form of [depth, temperature and pressure gradient] representing a single array containing the three independent variables and [BHP] representing the dependent output variable.

The data sample was split into a training dataset and a testing dataset in order to perform the model validation. The training dataset was further divided into batches to prevent over fitting of the model to the data. The batched dataset was then fed into the model which contains four hidden layers with fully connected nodes given as “self.fc = torch.nn. Linear (input nodes, output nodes)” and activated with the rectified linear activation unit (ReLU) function. The model was then compiled using the Adam optimizer and the Mean Square Error loss function at a learning rate of 0.0001 and a weight decay of 0.001. The codes are attached as Appendix B.

The feed forward neural network used in this model is a multilayer perceptron where, as data input occurs in the single node, the decision flow is unidirectional, advancing from the input to the output in successive layers, without cycles or loops.

2.4.2.1. The perceptron. To understand the function of neural networks, you need to understand the performance and characteristics of the perceptron. The operation of the perceptron is performed by evaluating the function using a weighted input sum. Weights which influence the individual input variables are determined by mathematically changing the input weights to obtain output that closely matches the desired output result. This process is called weight training and is performed using real input and output data from the training group. A non-linear function called the “transfer function” is used to estimate the weighted sum of the input data and generate an output response for the perceptron or set/target value. The idea of perceptron was developed as a tool for classifying samples according to the values of predefined input variables [37].

The obvious limitation of the use of perceptron is that it can only solve classification problems that can be linearly divided. This limitation is overcome by a multi-layer perceptron network. The input layer only works for storing values of input variables. In the “hidden” layer, the perceptron blocks are arranged in parallel, which allows numerous hyper-plane tests to be performed for a set of linear variables in the input vector. In the output layer, the results of the hyper-plane tests from the hidden layer are combined. As a result, the parallel perceptions in the “hidden” layer are used to make parallel decisions about class membership, and the results of these tests of the hidden level are evaluated at the “output” layer [37]. This is due to the fact that the non-linear resolution surface, developed by using the multilayer network configuration, uses a combination of hyper-plane tests to construct class boundaries.

The multilayer perceptron network was adopted for this study in developing the BHP predictive model from field data.

2.4.2.2. Feed Forward Model architecture. The deep learning neural network model is built on python using the PyTorch library which provides high level features such as tensor computing and deep neural networks built on a tape-based automatic differentiation system. The model is a feed forward neural network with three (3) hidden layers consisting of 100, 50 and 50 fully connected nodal points respectively (Fig. 1). The fully connected neural network structure was designed to accept the input parameters (depth, temperature & pressure gradient) and return the Bottom Hole Pressure as output.

The training algorithm used in this method is the gradient descent algorithm which is a first-order iterative optimization algorithm for finding a local minimum of a differentiable function. The transfer function adopted is the Rectified Linear activation Unit (ReLU) function which is defined as the positive part of its argument: $f(x) = x^+ = \max(0, x)$, where x is the input to a neuron. The ReLU function is thus represented graphically as shown in Fig. 2.

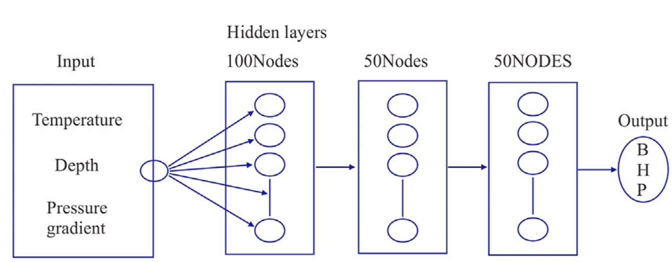

Fig. 1. Feed forward model architecture.

2.5. Data used for this study

For any regression model, including machine learning methods, the reliability, robustness, and universality of the model predictability is largely dependent on the quality of the input data set on which the model was developed. Yarveicy and Ghiasi [40] noted in their study that, "the precision and credibility of any predictive tool is believed to be related to the universality and superiority of the employed databank for their basis". A total of eight (8) oil fields data from Niger Delta fields was acquired for this study, and six (6) was used for training and two for validation of the developed model. In dealing with measurement data, it is crucial to understand that all measurements of physical quantities are subjected to uncertainties. The aim in any measurement is to make the error as small as possible, and some of these errors result in inaccuracy in determining the exact depth, wellbore coordinates, inclination and azimuth at survey site. These errors can be classified as gross, random and systematic errors.

For data acquisition, downhole measurement-while-drilling (MWD) hardware consists of sensors built into a drill collar positioned near the bit. In a typical turbine-powered MWD system, data are sent directly to the surface by mud telemetry, which utilizes the column of fluid inside the drill pipe as a transmission line for digital acoustic signals. Downhole measurements recorded by the sensors are transmitted through the mud as positive or negative pressure pulse or as a continuous, fixed frequency pressure wave. The mud telemetry signals are detected with pressure transducers in the standpipe. The digital signals are then recorded by a computer. Data are converted to engineering units and processed to generate depth-based output. These telemetry connections can be compromised, hence leading to measurement errors imposed by factors such as high flow rates in the drill string and the nature of the mud, especially electrically conductive muds.

The data set collected for this study includes the general information of the field, general data, well data, depth control data, gauge information, gradient QA/QC plot, BHP program, gradient data and plots, and the detailed distributions of the geo-lithofacies (sandy soil, shale clay, sandy clay, sandstone, clay, and sand silt) can be found in the study by Okoro et al. [41]. Figs. 3 and 4 show the field measured BHP variation with depth and pressure gradient. After an initial analysis with the correlation heat-map (Fig. 5), some of the parameters were discarded due to their inconsistency or existence as outliers and some were not relevant in developing the desired model for BHP prediction. The six oil field data were acquired using measurement while drilling device to collect surface measurements of the downhole pressure data while drilling. For the two case studies, measured field data of the wellbore filled with gasified mud system was utilized, and the wellbores were drilled using rotary jointed drill strings. During circulation (that is, drilling operation), the bottom hole pressure equals to the sum of hydrostatic pressure and frictions generated through the drilling fluid circulating system. Thus, the drilling fluid density at each hole section will not be used in developing the models, since it has been captured.

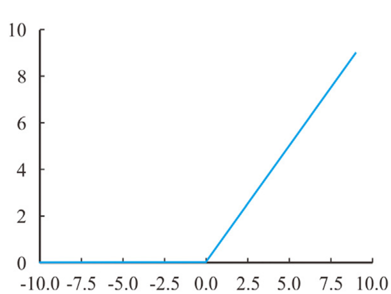

Fig. 2. ReLU plot.

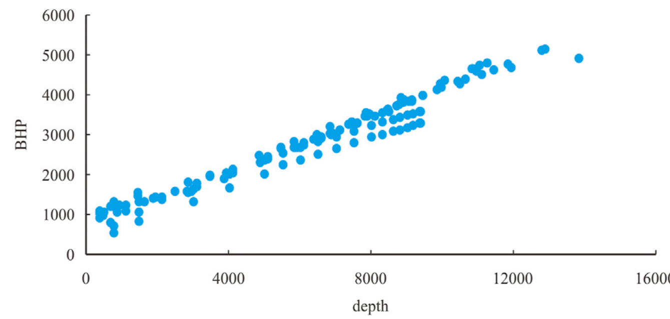

Fig. 3. Variation of Field measured BHP with Depth.

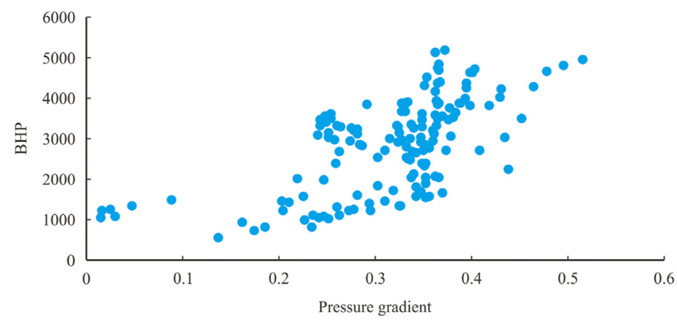

Fig. 4. Variation of Field measured BHP with Pressure Gradient.

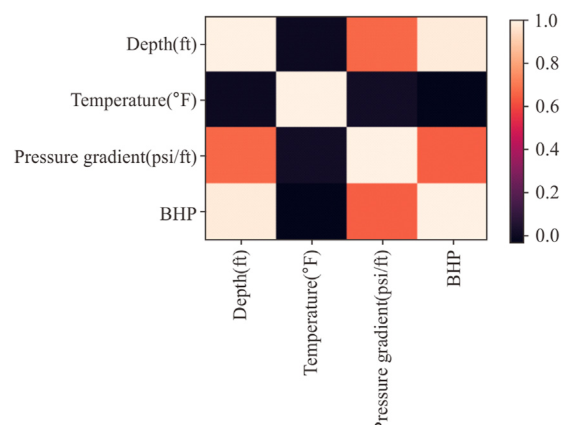

Fig. 5. Data correlation Heat-Map for the Measured Field Data.

In certain kinds of experimental or field situations, the researcher has the capability of obtaining repeated observations on the response for each value. Repetitions enable the experimenter to obtain quantitative information concerning the appropriateness of the model. In fact, if repeated observations are generated, the experimenter can make a significance test to aid in determining whether or not the model is appropriate [42]. The dataset consisted of 550 data points and split into 80% training dataset and 20% testing dataset. Literature has shown the influence of the size of the training data set on the quality of AI model generalization capacity [43]. Other studies have also shown that the prediction performance of some models will improve apparently when dataset enlarges, in which more data are needed for robust nonlinear or linear models with construction of new inputs [44,45]. Kandel and Castelli [46] concluded that a higher batch size does not usually achieve high accuracy, and the learning rate and the optimizer settings used will have a significant impact as well. Lowering the learning rate and decreasing the batch size will allow the neural network to train better. Training of deep learning networks is usually provided by stochastic gradient descent. The iterative optimization approach minimizes the given objective function using batch samples taken from data sets. Batch size has an important role in this optimization technique. The training dataset in this study was further divided into batches of 10 for effective training.

The statistical information of the field measured dataset used in the study is given in Table 1.

According to Table 1, the formation depths are in the range of 0–13,851 ft, the pressure gradients were within 0–0.7438 psi/ft and the measured bottom hole pressures are in the range of 534.63–5144.75 psi. An optimized UBD operation requires the use of appropriate equipment to drill, complete the well within the shortest period possible in the most efficient manner. Determining the optimum operational drilling conditions to achieve minimum pressure drop in the drill string, across the drill bit in order to generate BHP capable of providing efficient hole-cleaning and however, transport drill cuttings to the surface effectively plays very significant role in drilling operation.

3. Evaluation of the proposed model

As a result of the modelling work done in this study to predict bottom hole pressure, one model was developed. In this section, the criteria used to assess the performance of the model developed in this study are the coefficient of determination (R^2) and error analysis. The robustness of the model developed in this study was evaluated using two fields as case study.

3.1. Case study 1: field A

Field A is an onshore oil field and from the well schematic, the maximum deviation angle and depth was 11°F at 14857 ft. After developing a predictive model and algorithm, it is important to quantify the performance and how accurately the model fits to future observations. One of the simplest approaches in calculating the performance of a model is estimating the error between the predicted value and the actual value. There are many methodologies that take this difference and further exploit meaning from it, because quantifying the accuracy of a model is an important step to justify its usage.

Figs. 6 and 7 show comparison of the actual measured bottom hole pressure of the field and the predicted BHP from the Extra tree and Feed forward models for Field A. It should be noted that the number of digits of these parameters are determined using

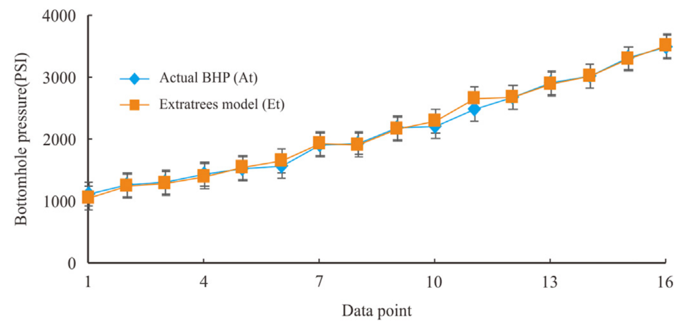

Fig. 6. Actual measured BHP vs Extra Tree Model predicted BHP for Field A.

statistical analysis. This refers to a vast set of tools for understanding data. This analysis was carried out for the overall errors of the process of optimization. The coefficient of determination (R^2), mean absolute percentage error (MAPE), which measures the accuracy of the predicting model, mean absolute error (MAE) that takes the absolute difference between the actual and predicted value and finds the average, and mean squared error (MSE) used to determine the errors by which the proposed predictive model differs from actual values of BHP, are the statistical parameters utilized to assess the accuracy and the reliability of the developed Extra tree model for the prediction of the bottom hole pressure in the field during underbalanced drilling. No one method dominates all others over all possible data set.

In order to evaluate the performance of the proposed model on the measured field data set, there is need to measure how well its predictions actually match the field data; thus, the error analysis results for the presented Extra Tree model prediction (Fig. 6) and Feed forward model prediction (Fig. 7) are tabulated in Table 2. According to Table 2, the average of the squared difference between the predicted BHP values and the field measured BHP values (MSE) was small (0.3) showing that the predicted BHP responses are very close to the measured field BHP. This shows that the predicted and the measured BHP did not differ substantially. The extent of model fitness to field data was actualized using the R^2 obtained from statistical analysis, and it takes the form of a proportion (proportion of variance under investigation). The R^2 Statistic for the predict field A BHP was close to 1 (0.9945). This indicates that a large proportion of the variability in the BHP has been explained by the regression. It also shows that there is a good relationship between the proposed Extra Tree model for BHP prediction and the selected dependent variable. The mean absolute percent error (MAPE) 2.03 for Field A shows that on average, the proposed Extra Tree model for BHP is 2.03% off from the measured field values. The accuracy measured for the MAPE is based on one-period-ahead residuals. At each point in time, the model is used to predict the value for the next period in

Table 1
Statistical details of the field measured data used in this study.

Parameters	Depth (ft)	Pressure gradient (psi/ft)	Bottomhole pressure (psi)
Mean	6327.98	0.307454	2829.821
Std	3461.064	0.116363	1139.534
Min	0	0	534.629
25%	3483	0.266725	1827.587
50%	6998	0.337	2991.484
75%	9018	0.365525	3627.524
Max	13851	0.7438	5144.75
90% CI	5920–6830	0.306–0.331	2680–2980
95% CI	5830–6910	0.304–0.334	2650–3010
99% CI	5660–7080	0.299–0.338	2590–3070

*CI – Confidence Interval.

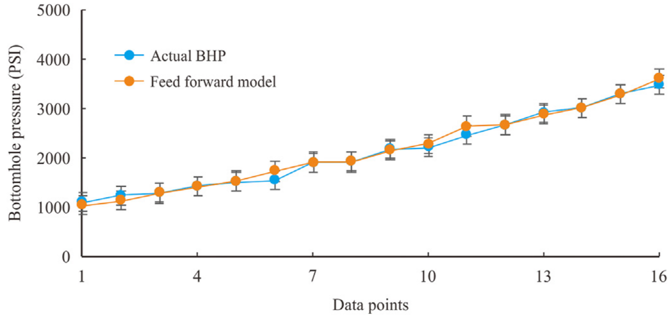

Fig. 7. Predicted BHP from feed forward model and actual field measured BHP for field A

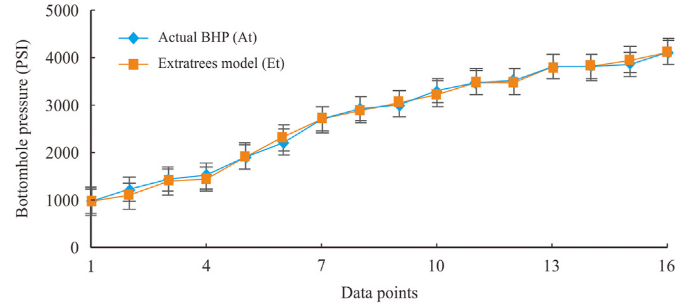

Fig. 8. Comparison of actual measured BHP with Extra Tree Model predicted BHP for Field B.

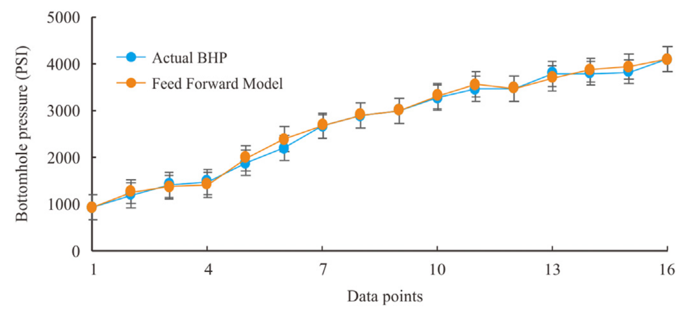

Fig. 9. Comparison of actual measured BHP with Feed Forward Model predicted BHP for Field B.

time. The difference between the predicted values (fits) and the actual are the one-period-ahead residuals. Because of this, the accuracy measured, provides an indication of the accuracy one might expect when one forecasts out 1 period from the end of the data. The mean absolute error of the measured Field A BHP and Extra Tree model predicted value is 9.1345. Finding the mean absolute prediction error (MAE) value is important because it does not allow for any form of cancellation of error values; it shows that the average difference between the field-measured and model predicted BHP is 9.1345 psi. MAE is based on the loss function, and can be viewed as a robust measure of predictive accuracy.

Table 2 also shows the error analysis results for the presented Feed forward model prediction (Fig. 7). The mean squared error (MSE) for predicted and measured BHP was 0.4132 for Feed Forward model, and this is higher than the MSE of the Extra tree model (0.3432). This shows that there is a variance or deviation between the two BHP predictive models. The R^2 value of 0.9895 shows a good fit for the proposed Feed Forward model, but, the Extra Tree model fit shows a better trend than the Feed Forward Model. The MAE of the measured BHP and Feed Forward model predicted value gave 11.0013, this means that the average difference between BHP values under consideration is 11.0013 psi. The MAPE shows that the actual and predicted BHP values for Field A is 3.99% off from the measured field values if Feed Forward model is used for prediction. The general observation from the trends of statistical result shows that, the Extra Tree model predicted the field's bottom hole pressure spikes and pattern better than the Feed Forward model.

3.2. *Case study 2: field B*

Field B is a swap oil field of survey depth, 9408 ft (measured depth) and the well-elevation 38.0'. Figs. 8 and 9 show a comparison of the actual measured bottom hole pressure of the field and the predicted BHP from the Extra Tree and Feed Forward models for Field B.

Table 2 shows the error analysis results for the presented Extra Tree and Feed Forward model predictions (Figs. 8 and 9) since the relationship among the variables are not deterministic. The mean square error (MSE) for the predicted and measured BHPs for Extra Tree and Feed Forward models are 0.3245 and 0.4002 respectively. These values are higher than the MSE values obtained from Field A. The R^2 value of the two models was close to unity, showing that a good measure of the proportion of variability was explained by the proposed models. The MAE for Extra Tree and Feed Forward models for Field B are 10.3939 and 10.9788 respectively. Thus, the average difference between the field measured and model predicted BHP is 10.3939 and 10.9788 psi respectively. This provides a protection against outliers. Also, the average of the percentage errors using MAPE for Field B are 2.028 and 3.90 for the Extra Tree and Feed Forward models respectively. This shows that the proposed Extra Tree model for BHP is 2.03% off from the measured field values, while the Feed Forward model is 3.90% off the actual value.

The high values of R^2 for the two models (Table 2) suggest the relative capabilities of these modelling techniques in terms of goodness of fit and statistical analysis. The magnitudes of MSE and MAPE predicted for BHP predictions of all the two models are low, with the lowest prediction error values for the two fields used for validation belonging to the Extra Tree model. The MAE of the Extra Tree model for both fields are lower than that of the Feed Forward model, further showing the higher robustness and precision of Extra Tree model relative to the Feed Forward model. It goes to show that, there is a good prediction performance for the evaluated case studies given a good model fit.

Table 2
Extra Tree Model Error analysis for Fields A and B.

Parameter	Test	Extra Tree Model		Feed Forward Model	
		Case study A	Case study B	Case study A	Case study B
R square	0.9889	0.9945	0.9975	0.9895	0.9911
MAPE (%)	3.42782	2.144697	2.02829	3.9871	3.8999
MSE	1.4233	0.3432	0.3245	0.4132	0.4002
MAE	29.9618	9.1345	10.3937	11.0013	10.9788

Spesivtsev et al. [47] developed a neural network containing 100 and 50 hidden units for the prediction of downhole pressure. The predicted results were consistent with the present study; the model is capable of predicting the BHP behavior for the dataset that were not used for training. Although this study's neural network models performed better in terms of predicted data accuracy, because Spesivtsev et al. [47] proposed model struggled to predict some particular dataset, and they were able to identify the particular dataset that were challenging for the algorithm to predict. Jahanandish et al. [48] also developed an artificial neural network model for predicting bottomhole pressure, and the result showed 9.5% mean absolute error and 0.92 correlation coefficient, but the proposed models in this study have mean absolute error ranging from 10.39% to 10.97%, and 0.98 to 0.99 correlation coefficient. Also, prediction performances of Ansari et al. [49] and Mukherjee and Bill [50] that have been used by the industry gave a correlation coefficient of 0.89 and 0.87 respectively for the dataset. Ping et al. [51] recorded mean absolute errors of 10% and 10.5% with the Hasan-Kabir model and the modified version of the Ansari model respectively, in predicting wellbore pressure.

Thus, based on the data gathered from comparing the absolute errors and correlation coefficients of the aforementioned models with those of the newly developed models, the newly developed models performed optimally with the listed correlations and mechanistic models.

3.3. Pressure profile for underbalanced drilling (UBD)

When drilling, determining the pressure profile down the hole is of utmost importance. By circulating the fluid with a mud pump during drilling, energy is transferred to the fluid used in the drill bit for drilling to remove formation cuttings from the surface of the bit and move the cuttings from the wellbore annulus to the surface. To perform these functions, it is very important to maintain the pressure of the circulating fluid during drilling. In addition to maintaining high downhole pressure, maintaining hydraulic pressure is essential for effective well control while drilling [52]. The pressure of the circulating fluid is determined by the hydrodynamic properties of the fluid. The reliability assessment of the managed pressure drilling system has been studied by Sule et al. [53].

In the case of unbalanced drilling, the well pressure generated must be within the pressure window. The pressure at the bottom of the well should not be too low to affect the stability of the well, nor too high to avoid the loss circulation and increase the risk of formation damage, as is typical of overbalanced drilling. Figs. 6-9 shows the pressure trends that must be maintained to avoid severe economic and operational consequences. The Extra Tree and Feed Forward models showed a good match and it is possible to achieve good underbalanced drilling operation with small deviations from the selected operational criteria. Pedersen et al. [54] highlight the need for such good predictive models for accurate control of pressure, and also stated multiple reasons why good pressure control is needed during underbalanced drilling.

Data acquisition is an important aspect of the drilling program, and Figs. 6-9 shows the trends of the bottomhole pressure for the two case studies. To a large extent on the successful production and depletion of a reservoir depends upon the successful drilling and completion operations applied to a well. Underbalanced drilling was initially adopted for resolving drilling instabilities due to long hole section with narrow pore pressure and fracture gradients of the target formation of interest. The pressure window is said to be narrow and this was evidence in the ratio of pore pressure to vertical stress moving close to lithostatic condition. The predicted BHP shows the range of pressure that must be maintained to successfully land the wellbore to the true depth. The downhole pressure will be maintained below the effective reservoir pressure at all points along the open hole section. Thus, minimize bottomhole pressure transit even during connection time. The predicted BHP will also help in developing UBD operational envelope that will help maximize the chance of success.

Both models proposed in this study assumed that the underbalanced drilling process begins after the downhole pressure drops to the specified pressure, the model ignores the unloading process. Instead, considered that the initial conditions are those that will be achieved after the gasified drilling fluid system has already reached the desired downhole steady state conditions. The UBD operation must be designed such that it is possible to achieve underbalanced condition throughout the operation within the operational restrictions. According to Fattah et al. [55], if planned and applied correctly, underbalanced drilling can address problems of formation damage, poor penetration rates, and loss circulation. Li et al. [56] concluded that underbalanced operation does not guarantee the improvement of horizontal well's extension ability, because it mainly depends on the relationship between the bottomhole pressure and its corresponding critical point. The key to underbalanced operation is to control the bottomhole pressure, and the key to controlling bottomhole pressure is to accurately calculate or predict the downhole pressure behaviour. Thus, the application of this study proposed models for predicting bottomhole pressure trends.

4. Conclusions

Determination and prediction of bottom hole pressure (BHP) in underbalance drilling (UBD) operation is vital for the management of the integrity of well lines and mitigation of formation failures. This study used data obtained from six fields to train and develop two models based on machine learning. These data–driven machine learning approach depends on the implementation of the concept of gathering relevant bits of information within the decision tree and feed forward multi-layer perceptron to predict the BHP of a well scheduled to undergo underbalanced drilling. The two approaches were selected to capture the fluctuations in actual BHP and deal with the relative predictable uncertainties. The algorithms were used to perform data mining and statistical analyses in order to determine trends and patterns in the observed and trained data. These models were further validated using data from two fields. The statistical results obtained using MSE, MAPE and MAE show that both models predicted the BHP trends in Field B more than Field A. The overall result shows that the proposed models can serve as a predictive tool for managing and handling of bottom hole pressure while conducting underbalanced drilling. These models gave a significant prediction of the possible spikes in actual bottom hole pressure which are often ignored in other models proposed in literature. The results obtained demonstrate the potentials of these techniques for integrity management and ability to predict spikes in BHP. The developed models can be used to develop intelligent controllers or smart techniques that allow for the efficient management, prediction and control of BHPs during underbalanced drilling of oil/gas wells. Extra trees are data mining techniques, which use tree like structures to classify a set of data into various predefined target values that are in turn responsible for its higher robustness and precision.

Declaration of competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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