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APPLICATION OF MACHINE LEARNING TO DECLINE CURVE ANALYSIS (DCA) FOR GAS-CONDENSATE PRODUCTION WELLS WITH COMPLEX PRODUCTION HISTORY DUE TO ADD-ON PERFORATION OF NEW RESERVOIRS

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Summary

For every oil and gas operator, DCA plays an essential role since it provides crucial information for production planning and reserves estimation. DCA is the analysis of the decline in production rate or pressure over time, which can be done by fitting a curve through production or pressure historical data points and making a forecast for the well based on the assumption that the same declining trend will continue in the future. However, the conventional DCA method has been shown to have some limitations. On the other hand, machine learning has been vigorously and extensively researched in the last decade; its applications can be found in every aspect of life as well as in the oil and gas industry. Therefore, it is the ideal time to study the application of machine learning to DCA, to complement this important analysis. In this case study, machine learning was used to predict the decline of wellhead pressure, thereby determining well life as well as estimating reserves. The method was applied to 2 wells with very complex production histories due to add-on perforation of new reservoirs. The prediction was verified to have high reliability by comparison with dynamic modeling results.

Key words: Machine learning, decline curve analysis, wellhead pressure, production forecast, reserves.

1. Introduction

For an oil and gas operator, DCA plays an indispensable role by providing predictions about the productivity and reserves of the well, which are the key input for planning operation, business, and evaluating reserves. The standard procedure of DCA contains two elements. First, the historical data points are matched with a curve of 3 types namely hyperbolic, harmonic, and exponential. Then, once the production history is matched, the DCA model can give prediction of pressure and/or production of the selected well, based on the assumption that the same declining trend will continue in the future. The result from DCA can help determine when the well can no longer produce and estimate the reserves of the well at the time of abandonment. As illustrated in Figure 1, the black part of the decline curve passing through the blue data points represents the history matching process, the red part is the forecast results for the future. Physically, the production and pressure of wells decline with time, eventually leading to well abandonment. Despite many improvements that have been made since the first DCA model introduced by Arps in 1945 [1], the modern-day process of DCA is still

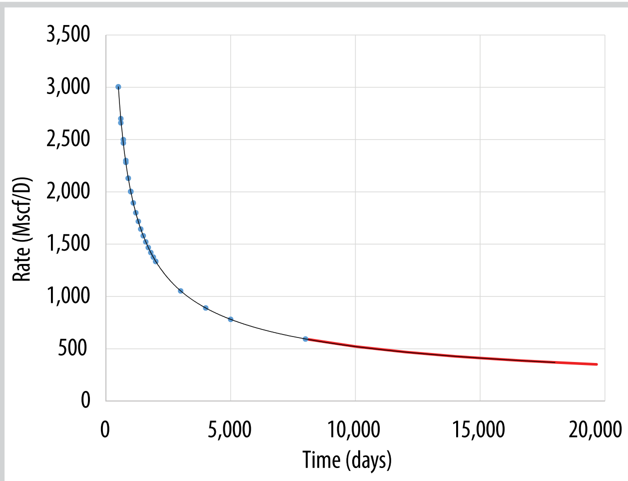

Figure 1. *A simple example of DCA.*

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complex work requiring much time and effort. BIENDONG POC is currently performing DCA in the conventional way, which has shown a few limitations. Moreover, the results are affected by subjective assessment of the analyst. Inspired by the strong development of machine learning in recent years, the authors realize that this is the right time to apply machine learning to DCA. In recent years, machine learning has permeated the global oil and gas industry, for example for lithofacies classification [2, 3], depositional facies prediction [4, 5], history matching [6, 7], and virtual flowmeter [8]. Regarding DCA, outstanding successful applications in production forecasting have been made. In 2019, Lee et al. published a case study in which a long short-term-memory (LSTM) model was constructed, trained, tested, and then utilized to perform DCA [9]. A dataset of 315 wells in the Duvernay formation, western Canada, was studied. The model was tested on a random sample of 15 wells, while the remaining 300 wells were designated for training purposes. The testing results of 15 wells showed that the model could predict production with higher accuracy than the hyperbolic DCA. However, the model had a limitation that it was designed for short-term forecasting (1 month into the future). In another study, Zhan et al. used data from more than 300 unconventional oil wells with 2 years of production history for each well to build two LSTM models, one to forecast the decline in production rate and the other to predict cumulative production [10]. For each well, the production history of the first 3 months was used to train the model and the remaining 21 months was used for testing. To overcome the problem of error accumulation in time series prediction and the challenge of capturing the steep production decline at the beginning, in addition to tubing pressure and oil rate, 12 wells with production rates similar to the analyzed well were selected from the database and translated into additional machine learning features. The results from the LSTM models showed over-prediction for the production rate and under-prediction for the cumulative production. Therefore, the authors combined the two models using weighted averaging to achieve better cumulative prediction results.

In another study about the application of machine learning in regression analysis, Han et al. used 3 different supervised learning models including random forest (RF), gradient boosting machine (GBM), and support vector machine (SVM) [11]. The authors used data collected from 129 dry gas horizontal wells in the Eagle Ford basin, Texas, USA, including completion and reservoir parameters to forecast the cumulative gas production after 36 months. Variables importance analysis and k-fold cross validation were used to prevent overfitting. For all three models, 80% of the data was used for training, the remaining 20% was used to test the accuracy of the model. Forecast results from all three models were compared with actual data and they showed that the RF model had the highest predicting accuracy among the three models in the study.

In general, the machine learning models introduced in the aforementioned studies had the same limitation that they could not capture sudden changes in the production or pressure history. Failure to history match yields a negative impact on the reliability of the forecast results. In this study, we aim to overcome the above limitation, thereby making more reliable predictions of wellhead pressure and reserves.

2. Methodology

The first step of the study is data preparation. Then the complete dataset of each well will be split into training/testing datasets. Several machine learning algorithms are then tested and evaluated to determine the optimal algorithm. Finally, the machine learning model will be used to predict the decline in wellhead pressure, thereby determining when the well depletes and its reserves at the time of abandonment. This paper is part of the results of the research project to improve the efficiency of management and production of the Hai Thach - Moc Tinh gas-condensate field [12].

The machine learning model in this study is developed to perform two tasks. The first task is to generate a decline curve that matches historical data points. The second task is to predict the future trend of wellhead pressure decline when subjected to a constant gas production rate, thereby estimating the time when the wellhead pressure reaches the minimum threshold. In this study, two gas-

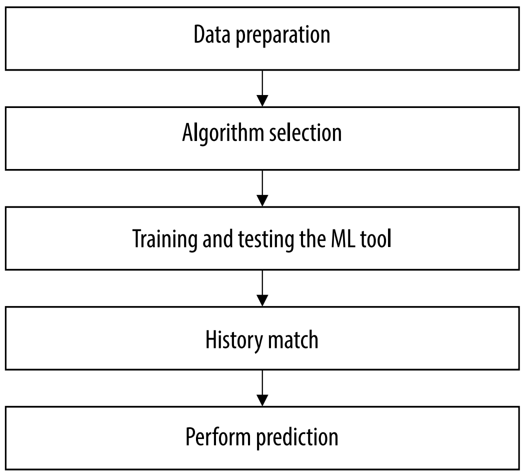

Figure 2. *Flow chart of the methodology.*

condensate wells with sudden changes in production history due to add-on perforation of new reservoirs are selected for the application.

2.1. Data preparation

The data used in this study was historical data of the two selected wells, including the following types: day/month/year data; number of opening hours in a day (uptime); gas rate; and wellhead pressure (WHP). In order to obtain a representative data set, the authors used only data points with 24 hours of well opening in a day.

2.2. Algorithm selection

Several algorithms are initially selected to build the machine learning model including LSTM, extreme gradient boosting (XGBoost), linear regression, polynomial regression, and piecewise regression. The XGBoost, linear regression, and polynomial regression algorithms quickly fail at the history matching steps because of too many errors, especially at abrupt changes in the pressure history due to add-on perforation of new reservoirs. The LSTM model provides decent history matching results but is proven incompetent in predicting wellhead pressure decline. With piecewise regression, this algorithm uses the decision tree regression algorithm to group the data (bucketization) and the linear regression algorithm to find trends for each group. With this principle, the algorithm is suitable for datasets with many different trends, such as complex production history. Research on the application of the piecewise regression algorithm can be found in many topics related to all aspects of life. One of the notable studies is the research by Al-Azzeh et al., on the method of applying the piecewise regression algorithm to increase the accuracy of mathematical models [13].

2.3. Training and testing the machine learning model

To train the machine learning model, the production history of each selected well is used as input, with a frequency of one data point per day. Day/month/year data was converted to datediff format (number of days from the first data point). The training/testing split of 50/50 from the point when the wellhead pressure changes suddenly due to add-on perforation is used. During training, the error between the wellhead pressure predicted by the model and the actual wellhead pressure is calculated to check the accuracy of the model. This error is the basis for choosing the most optimal model to predict the wellhead pressure in the future.

2.4. Application of the machine learning model

For predicting when the wellhead pressure will reach the cut-off threshold, the entire historical data is used instead of the previous 50/50 split. The machine learning model is trained again on this new dataset to increase the accuracy of the prediction results. The error in this process is also calculated and used as a foundation of model selection for future forecasting. For the prediction part of each well, the datediff data is set to increase one day at a time while the gas production is kept the same as the last data point available. Finally, the most optimal model is used to forecast the decreasing trend of wellhead pressure in the future. In the scope of this study, the machine learning model is applied to two wells, HT-A and HT-F, to forecast the trend of wellhead pressure decline, thereby predicting the time of abandonment of the well and reserves at the time of abandonment.

3. Results

The results of testing extreme gradient boosting (XGBoost), linear regression and polynomial regression are shown in Figure 3 to Figure 5. As discussed in the above section, the mentioned algorithms quickly failed at the history matching steps with too many errors.

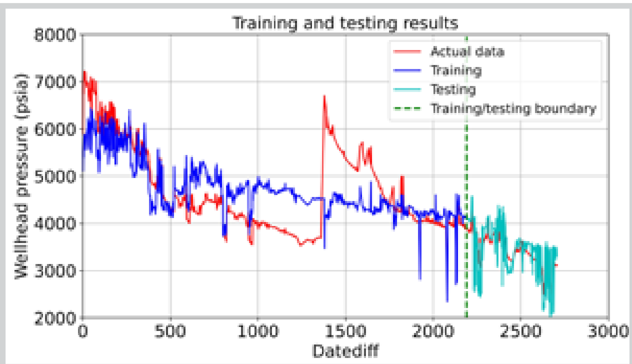

Figure 3. *Training/testing results for HT-F using XGBoost still have limitations.*

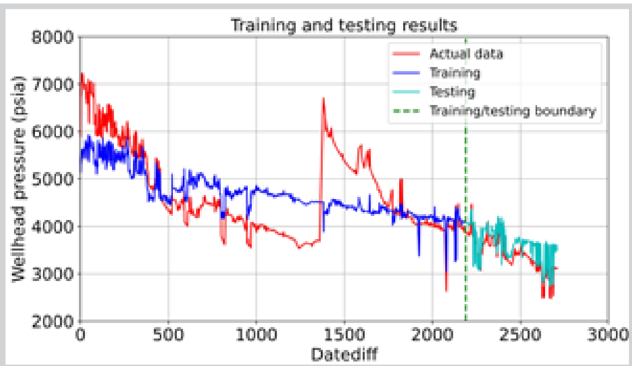

Figure 4. *Training/testing results for HT-F using Linear Regression still have limitations.*

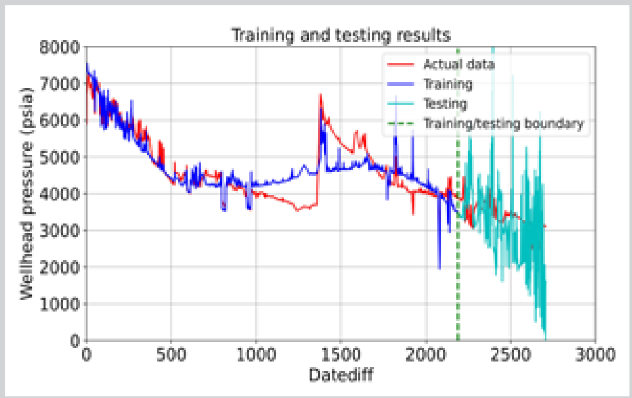

***Figure 5.** Training/testing results for HT-F using Polynomial Regression still have limitations.*

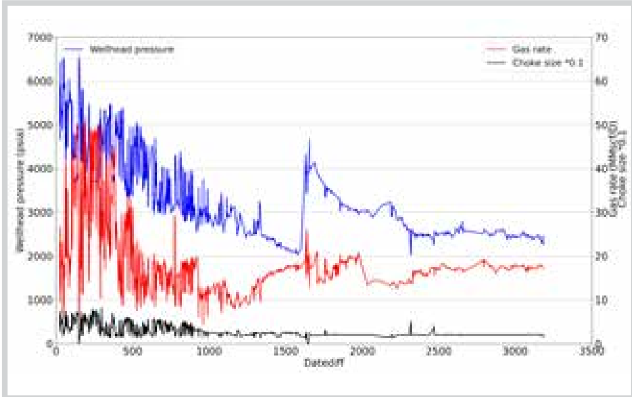

***Figure 6.** The production history of HT-A.*

3.1. Well HT-A pressure prediction results

Well HT-A started production in the second quarter of 2014. Initially, this well appeared to be a powerful producer with the gas rate as high as 50 MMscf/d and the wellhead pressure was approximately 7,000 psia. However, after 4 years of production, the wellhead pressure dropped to below 2,000 psia with the production of the well fluctuating around 10 MMscf/d. HT-A was add-on perforated in the third quarter of 2018, corresponding to a datediff of about 1,600. The results after the perforation campaign showed that at the same choke size of 20%, the wellhead pressure increased from approximately 2,000 psia to nearly 5,000 psia and followed a new decline trend (Figure 6). In addition, gas production increased from about 10 MMscf/d to about 18 MMscf/d.

The training and testing results show that the machine learning model matches the wellhead pressure historical data of the HT-A very well (Figure 7). The sudden change in the wellhead pressure curve caused by add-on perforation is also captured by the machine learning model.

As for the forecast results from the machine learning model (Figure 8) with a constant production rate of 18 MMscf/d, HT-A can sustain production until the fourth quarter of 2027. Meanwhile, the dynamic model predicts that HT-A would have the abandonment time one year earlier than what is foreseen by the machine learning model. The reason for this difference is the dynamic model could not match the last year of the historical data very well while the machine learning model matches this period with nearly perfect accuracy. In this case, the machine learning model is more reliable than the dynamic model. HT-A well reserves would reach 72 Bscf at the time of abandonment in the fourth quarter of 2027.

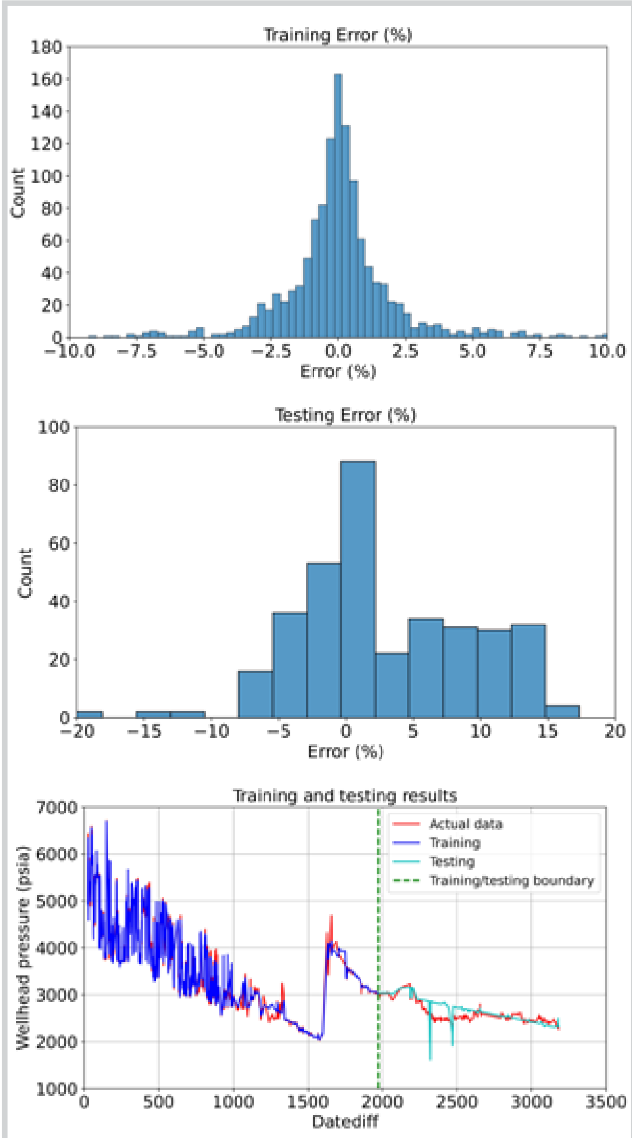

***Figure 7.** Training/testing results for HT-A.*

3.2. Well HT-F pressure prediction results

Well HT-F has been producing since the second quarter of 2015. The wellhead pressure of this well at

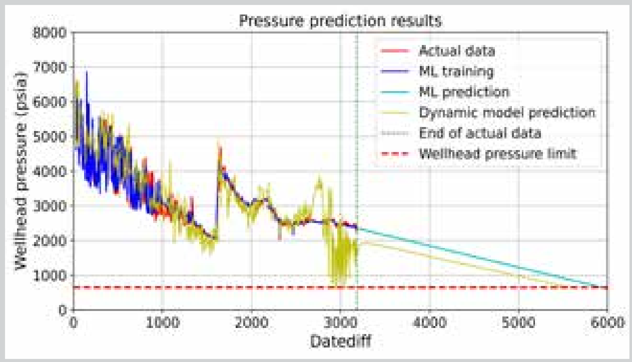

Figure 8. HT-A wellhead pressure prediction results.

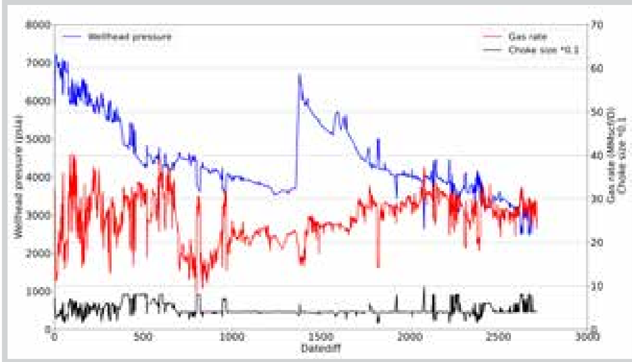

Figure 9. The production history of HT-F.

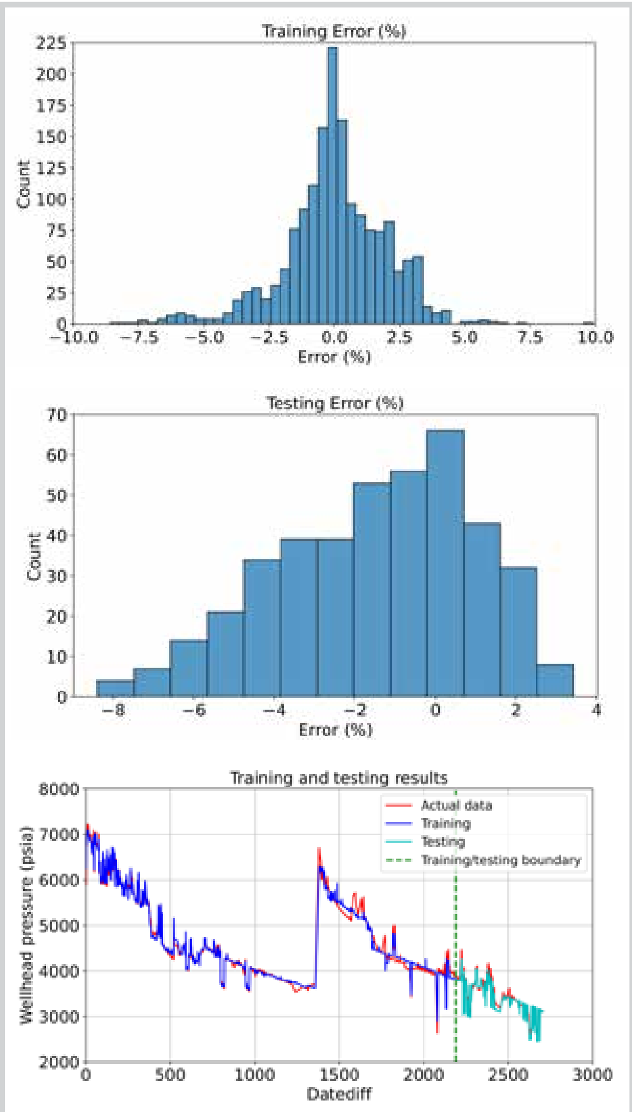

Figure 10. Training/testing results for HT-F.

the start of production was as high as 7,000 psia and dropped to below 4,000 psia after nearly 4 years. Add-on perforation was carried out for HT-F in the first quarter of 2019 to improve productivity, corresponding to a datediff of about 1,400. The results after add-on perforation

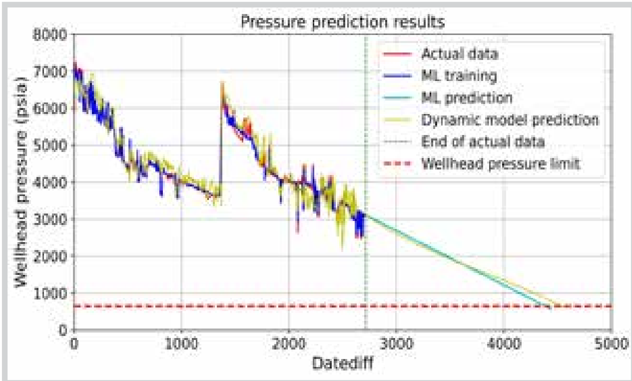

Figure 11. HT-F wellhead pressure prediction results.

showed that the wellhead pressure increased to nearly 7,000 psia, close to the initial value. Afterward, it declined in an entirely different trend compared to before add-on perforation. In addition, gas production also increased from approximately 20 MMscf/d to approximately 25 MMscf/d (Figure 9).

Similar to HT-A, the machine learning model is successful in matching the production history of HT-F well, including the sudden increase in pressure caused by add-on perforation, as shown in Figure 10.

The wellhead pressure of HT-F is forecasted using piecewise regression algorithm to reach the cut-off threshold in the second quarter of 2027 if it keeps producing with a constant rate of 25 MMscf/d, as shown in Figure 11. Unlike HT-A, throughout the production/pressure history, and forecasting period of HT-F, the machine learning model and the dynamic model are similar. Therefore, the results from both models have high reliability. The reserves of HT-F at the time of closing the well will reach 100 Bscf.

4. Conclusions

In this study, a machine learning model is developed and applied to perform DCA analysis. The machine learning model is succesfully applied to generate a pressure decline curve that matches the historical dataset including periods of sudden and significant pressure changes due to add-on perforation of new reservoirs. Finally, the machine learning model could provide a reasonable prediction of the time of abandonment for the selected wells, as shown by the comparison with the best dynamic models available.

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