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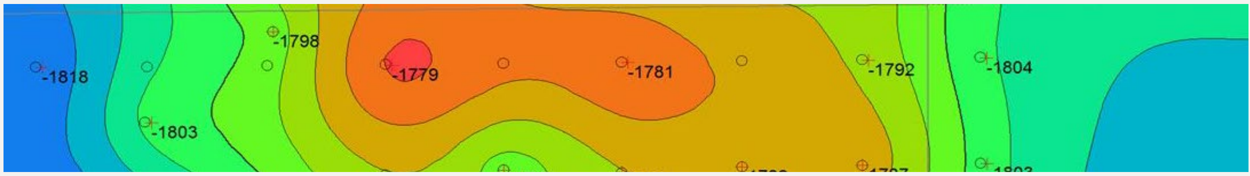

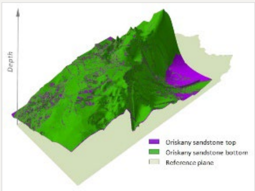

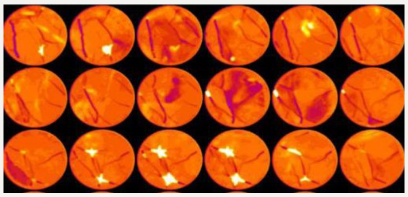

Evaluating Production Implications of Pressure Maintenance in Unconventional Oil and Gas Wells using a Machine Learning Modeling Approach: Case Study in the Permian Basin

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Disclaimer

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ACRONYMS AND ABBREVIATIONS

API	American Petroleum Institute
bbls	Barrels
DA	Data Analytics
ESP	Electric submersible pump
EUR	Estimated ultimate recovery
IP	Initial production
lbs	Pounds
LSTM	Long short-term memory
Mbbls	Thousand barrels
Mcf	Thousand cubic feet
MMcf	Million cubic feet
ML	Machine learning
MSE	Mean squared error
O&G	Oil and gas
Pe	Photoelectric factor
psi	Pounds per square inch
RMSE	Root mean squared error

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EXECUTIVE SUMMARY

The use of data analytics (DA) and machine learning (ML) to model subsurface processes in the oil and gas (O&G) sector has gained significant popularity as of late. One widely explored application is the use of ML-based models trained to replicate and forecast O&G production. The utility of developed ML-based models is dependent on the data quality used in the model development. Critical geologic, drilling, and well completion parameters are key to developing models that are representative of the systems they reflect and would offer utility when applied in practice. In the context of O&G production, ML models offer fast and accurate compliments to traditional reservoir modeling and simulation approaches and can be employed to explore the implications of different well completion, well placement, and production choices – thereby contributing insight that can be used to then inform operational decisions.

This study examines and implements the proprietary deep learning ML-based model (model) developed by Vikara et al. [1] for forecasting unconventional oil and gas production using well data from the Permian Basin. The model was developed using an exclusive dataset that includes time series data from an operator in the Permian Basin. The model is designed to jointly predict daily oil, gas, and water production for horizontal wells as a function of bottom-hole pressure drawdown, spatial placement across the study domain, and well-completion attributes. Key features in the dataset include geologic properties from well log data, detailed well hydraulic fracturing data, artificial lift design data, and well operating conditions. The model can predict daily production for oil, water, and gas with accuracy on the order of 79 percent (for water and gas) to 86 percent (for oil). The extensive input parameter set used in the development of the model provides the utility to test and evaluate multiple controlling features on associated production. These features include (but are not limited to) well completion attributes, placement (spatially, at depth, and wellbore trajectory orientation), and operational controls on production intensity (via pumping pressure downhole).

In this study, the model was explicitly applied to explore its utility to evaluate the impact of varying drawdown strategies on the production forecast of one of the wells from the Permian Basin dataset. Managing pressure drawdown has been identified as a way to improve estimated ultimate recovery (EUR) due to the stress-dependent nature of fractures in shale reservoirs. Research has shown that applying a lower pressure drawdown helps to maintain the reservoir conductivity, resulting in higher productivity over the life of a well. Historic bottomhole pressure data from the well over time was used as a benchmark from which to set more and less aggressive pressure decline rates as bounding modeling cases. All pressure decline rates/strategies were forecasted over 5 years, and the model was used to generate oil, water, and gas prediction over the same timeframe. Results indicate that rapid drawdown of pressure generates higher initial oil and gas production from the well. However, overall oil and gas production over the medium to long term from rapid drawdown strategies is lower compared to conservative drawdown strategies that sustain pressure. Rapid drawdown strategies resulted in lower water production over the life of the well compared to conservative drawdown strategies. This production forecast of the varying drawdown strategies could have significant operational

and economic implications, with contrasting perspectives between well productivity and profitability given typical oil and gas economics and the volatility in the oil and gas market.

1 INTRODUCTION

Technological advancements that have occurred over the past two decades through horizontal drilling and hydraulic fracturing have afforded the enabling components for producing hydrocarbon from unconventional shale gas, tight gas, and tight oil formations—key resources that are extensive in the United States. Horizontal wells drilled and completed in unconventional oil and gas reservoirs using hydraulic fracturing techniques account for the vast majority of hydrocarbon production in the United States (U.S.). [2] These techniques have been central in revolutionizing the energy system in the U.S. and are leading drivers in the growth of domestic oil and gas (O&G) production.

While the use of horizontal drilling and hydraulic fracturing in developing unconventional resources has boosted hydrocarbon production in the United States [3, 4, 2, 5, 6, 7], recovery factors from these resources remain relatively low. [8, 9] Opportunities exist to improve the productivity from these resources which would directly enable improved use of the nation's energy assets. At the well level, improved recovery could mean improved economics for operators, and potentially reduced environmental impact from O&G operations and lower greenhouse gas emissions from using fewer wells, water, and vehicle transport for production on a per-unit basis. One of the techniques that is been considered for improving the production of unconventional O&G resources is to produce the well using a lower-pressure drawdown.

O&G operators have reported that producing slower or using pressure maintenance schemes can be used as one of many potential strategies to enhance total production in unconventional reservoirs. Typically, in unconventional or hydraulically fractured reservoirs, a rapid pressure drawdown approach is employed to achieve high initial production (IP). However, controlling choke to optimize drawdown, shut-in time, and pressure cycling/maintenance has been a tactic to increase cumulative recovery (i.e., estimated ultimate recovery [EUR]) and overall recovery factors—but these outcomes may come at the expense of higher IPs. Controlling pressure drawdown results in a slower but more sustained production from the well. However, it is expected that limiting pressure drawdown will maintain the reservoir permeability, leading to higher production over the life of the well [10, 11]. Techno-economic analysis of O&G developments has shown that higher IPs from wells tend to correlate with greater economic returns. [12, 13, 14] Operators, therefore, typically employ rapid pressure drawdown strategies aimed to maximize initial production to achieve profitability objectives. However, research has shown that the implementation of rapid pressure drawdown to achieve high IP can reduce reservoir flow capacity and EUR. [15, 16] Therefore, effectively managing the production pressure drawdown can significantly improve the well productivity and reservoir performance.

Machine learning (ML) technologies have gained interest in the oil and gas sector because of their rapid prediction capability and capacity for effective generalization of complex systems. [17, 18] ML offers enormous potential for augmenting and enhancing traditional reservoir engineering strategies and can be applied to a multitude of use cases. For instance, several use cases exist where ML has been applied towards formation, stratigraphy, and lithology classification, inversion, and delineation [19, 20, 21], informing well drilling practices [22, 23], and evaluating the effects of hydraulic fracturing designs on hydrocarbon production and other well responses in unconventional reservoirs. [24, 25, 26, 27, 28, 29, 30, 31] In addition to these examples, many studies have focused on using ML for dynamic reservoir analysis by evaluating time series-based oil or gas production over the life of producing wells. These studies utilize different combinations of empirical data which include daily or monthly cumulative hydrocarbon production values over all or a portion of each well's productive life. Many of the relevant studies apply deep learning ML strategies to capture and generalize the intrinsic temporal or time sequence-based properties within the data. [32, 33, 34, 35, 36] Machine learning has even been applied for pressure drawdown evaluation in shale reservoirs [37], but examples in the literature are limited.

In this study, we aim to test the utility of a deep learning model developed by Vikara et al. (2022) [1] in evaluating pressure drawdown strategies using a case study well in the Permian Basin. The Vikara et al. (2022) study developed several supervised ML models for time series prediction of daily oil, water, and gas in a select area of the Permian Basin. Different predictive model variants were trained with specific formulations of proprietary and commonly-public data features. Each model variant makes predictions utilizing input attributes that span well performance (like pumping inlet pressure and days of production), completion (like water and proppant volumes used, fracture interval length, and the number of stages and perforation clusters), and spatial attributes (including well log data, drilling depth, and well spacing). Proprietary datasets were acquired by the National Energy Technology Laboratory (NETL) through an agreement with an operator with a large operational footprint in the Midland Basin. Their study used a quasi-experimental framework to quantify the impact of oil and gas operator-specific proprietary data on ML-based predictive model performance relative to using oil and gas datasets that may be more commonly publicly available. Their study found that model variants developed using input features not commonly available in the public domain (including lift inlet pressure, well log data, and stage-level completion data) held upwards of a 30 percent improved performance accuracy compared to a model formulation that utilizes only input attributes commonly publicly available. The Vikara et al. (2022) work helps demonstrate the utility of time series-capable ML modeling as a complement to existing oil and gas operational management strategies aimed at understanding the implications of well design, placement, and management choices on resulting production outlooks. The best-performing model proposed in their study utilizes downhole pump inlet pressure as a key input attribute. Therefore, that model variant can be simulated under various pressure management cases to test how the production response is reflected accordingly.

2 Study Approach

The objective of this study is to test the efficacy of the "Proprietary Model" (referred to as "model" from here on) proposed by Vikara et al. [1] towards evaluating the implications of pressure drawdown strategies using a case study well in the Permian Basin. The model is used to make predictions of three-stream fluid flows (i.e., oil, water, and gas) in a time series fashion. A single well is used as a case study for this analysis. The resulting three-stream production outlooks (at daily resolution) cover a series of different bottom-hole pressure drawdown and management cases. Oil, water, and gas production volumes can then be evaluated in the context of pressure drawdown. The following sub-sections discuss the data needs for the model, an overview of the model performance, and the approach to generate the various pressure drawdown cases.

2.1 Model Overview

The "Proprietary Model" proposed by Vikara et al. [1] is used as the base model for this analysis. The "Proprietary Model" gets its namesake because it contains an input feature set with data types that are not commonly available (in large quantities) in the public domain. Key proprietary input data features include downhole pump inlet pressure, electric submersible pump (ESP) size, detailed well hydraulic fracturing information (i.e., stages, clusters, sand and fluid treatment per stage, average and initial shut-in pressure, and specific chemical additives applied), as well log data of several geologic properties. Out of the three model variants developed and evaluated in the Vikara et al. [1] study, the "Proprietary Model" variant showed the highest overall performance for predicting daily three-stream fluid production. Additionally, because the model leverages downhole pump inlet pressure data,[a] the model seems to lend itself well to evaluating pressure management and associated production implications.

2.2 Model Data Summary and Data Processing Steps

A dataset of 318 horizontal wells in the Permian Basin (Exhibit 2-1) was used in the Vikara et al. [1] study, of which 240 wells were drilled in the Wolfcamp formations and 76 wells were drilled in the Spraberry and the Dean formations of the Permian Basin (Exhibit 2-2). The dataset was compiled from proprietary and public sources, and with some attributes generated through feature engineering. [1] The dataset contains features related to the location and orientation of the wells, reservoir geologies, well completion parameters, and production performance parameters (Exhibit 2-3). The wells in the dataset were drilled between January 2015 and August 2020, with production ranging between 1 day and 1,969 days.

A suite of legacy well logs in the study area was also evaluated and included in the ML workflow. The logs were evaluated to identify the tops of the different Wolfcamp, Spraberry, and Dean formations as well as other geologic properties including gamma ray, resistivity, photoelectric index, density, and neutron porosity values. Production wells were matched to logs based on relative aerial proximity using the *k*-means clustering approach. Through this process, geologic

[a] The feature importance assessment in the Vikara et al. [1] study indicated the pump inlet pressure is the most impactful input data attribute on daily oil, water, and gas production compared to all other input attributes.

data representative of the producing zones was harvested for wells that shared a common cluster group (Exhibit 2-1). Two key data preprocessing steps were performed before model training. The data were normalized to scale attribute data to a consistent range using min-max scaling to improve the efficiency of the ML algorithm [38, 39, 40, 41] and time-series sequence data was zero-padded to ensure that all wells had consistent sequence lengths. [42] Further description of the data summary and preprocessing steps is available in Vikara et al. [1]

Exhibit 2-1. Map of the study area in the Midland Basin, Texas, highlighting locations of wells used in this study.

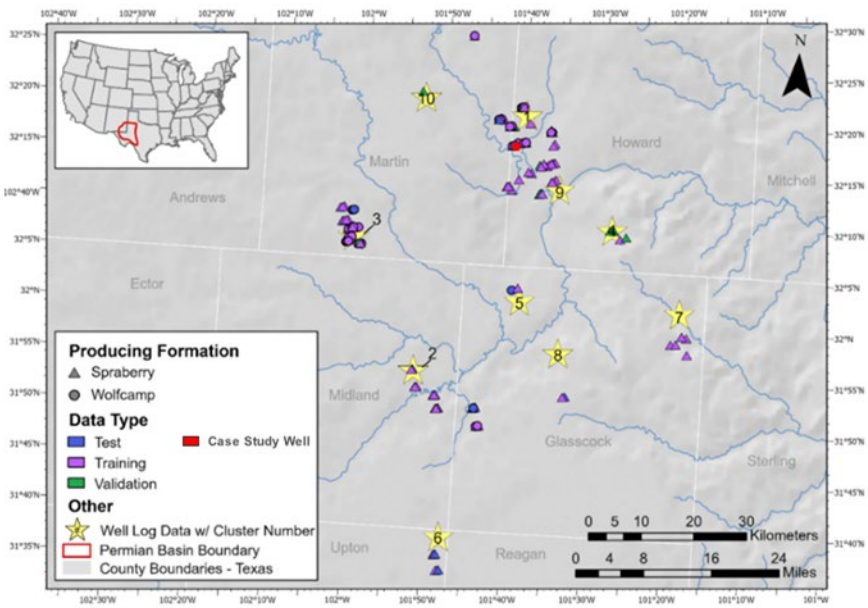


Exhibit 2-2. Stratigraphic overview for the Midland Basin, Texas, proximal to the study area

<table>
<tr><th>Era</th><th>Period</th><th>Epoch</th><th>Local Series</th><th>Stratigraphic/Formation Name</th><th>Reservoir Operational Name</th></tr>
<tr><td rowspan="13">Paleozoic</td><td rowspan="9">Permian</td><td rowspan="2">Guadalupian</td><td rowspan="2">Ward</td><td>San Andreas</td><td>San Andreas</td></tr>
<tr><td>San Angelo/Glorieta</td><td>San Angelo/Glorieta</td></tr>
<tr><td rowspan="5">Leonardian</td><td colspan="2">Clearfork</td><td>Upper Leonard</td></tr>
<tr><td rowspan="3">Wichita</td><td>Upper Spraberry</td><td rowspan="3">Spraberry</td></tr>
<tr><td>Lower Spraberry</td></tr>
<tr><td>Dean</td></tr>
<tr><td>Lower Leonard</td><td>Wolfcamp</td><td>Wolfcamp A</td></tr>
<tr><td rowspan="2">Wolfcampian</td><td colspan="2" rowspan="2">Wolfcamp</td><td>Wolfcamp B</td></tr>
<tr><td>Wolfcamp C</td></tr>
<tr><td rowspan="4">Pennsylvanian</td><td>Virgilian</td><td colspan="2">Cisco/Cline</td><td>Wolfcamp D</td></tr>
<tr><td>Missourian</td><td colspan="2">Canyon</td><td>Canyon</td></tr>
<tr><td>Des Moinesian</td><td colspan="2">Strawn</td><td>Strawn</td></tr>
<tr><td>Atokan</td><td colspan="2">Atoka/Bend</td><td>Atoka/Bend</td></tr>
</table>

Exhibit 2-3. Descriptive statistical summary of study dataset features (includes records before dropping instances where null values exist)

Feature Group	Feature	Data Class				Temporal Influence		Descriptive Statistics								Description
		Continuous	Category	Proprietary	Public	Static	Dynamic	Count	Mean	Stdev.	Minimum	25th percentile	50th percentile	75th percentile	Maximum	
Well Performance Attributes	Days Online (days)	X			X		X	160,649	444	358	1	169	354	638	1,969	Total days since wells were turned are online (under production); also include days well are offline (shut-in)
	Oil (bbls)	X			X		X	153,726	292	264	1	115	205	382	2,795	Daily oil production volume for each well
	Gas (Mcf)	X			X		X	149,504	588	416	1	279	499	813	4,031	Daily gas production volume for each well
	Water (bbls)	X			X		X	155,798	662	692	1	215	402	834	12,941	Daily water production volume for each well
	Pressure (psi)	X		X			X	109,888	943	594	0	583	779	1,092	5,444	Daily inlet pressure of the artificial gas lift system (typically ESP) for each well
Well Completion Attributes	Perforated Interval (feet)	X			X	X		318	9,042	1,491	998	7,627	9,575	10,177	14,686	Total length of the horizontal (i.e., lateral) section of a well that is perforated
	ESP Size (rating)	X		X		X		316	2,462	1,677	0	1,750	2,700	3,550	5,800	Flow rate of the ESP installed on the well
	Stages (count)	X		X		X		318	55	10	6	48	54	60	87	Amount of hydraulic fractured zones on each well
	Clusters per Stage (count)	X		X		X		318	8	2	4	6	8	9	13	Average amount of perforation clusters per stage of each well
	Shots per Cluster (count)	X		X		X		318	5	1	3	4	6	6	12	Volume of perforation shots per perforation cluster for each well
	Fluid per Cluster (bbls)	X		X		X		318	1,071	303	517	833	1,056	1,268	2,300	Average volume of fluid per perforation cluster for each well
	Sand per Cluster (lbs)	X		X		X		318	43,981	10,680	9	35,614	44,406	50,530	90,086	Average volume of proppant per perforation cluster for each well
	Initial Shut-in Pressure (psi)	X		X		X		318	3,176	2,208	1,133	2,499	2,984	3,630	39,450	Average initial shut in pressure for each well during the hydraulic fracturing process
	Average Treatment Pressure (psi)	X		X		X		318	7,365	711	5,032	6,928	7,428	7,856	9,049	Average treating pressure for each well during the hydraulic fracturing process
	Resin-coated Proppant Volume (lbs per foot)	X		X		X		318	103	59	0	89	126	141	251	Average volume of resin-coated proppant pumped per perforated interval for each well

Feature Group	Feature	Data Class				Temporal Influence		Descriptive Statistics								Description
		Continuous	Category	Proprietary	Public	Static	Dynamic	Count	Mean	Stdev.	Minimum	25th percentile	50th percentile	75th percentile	Maximum	
	Surfactant Use (yes/no)		X	X		X		318	Yes = 309				No = 9			A non-emulsifier or surfactant agent used during the hydraulic fracturing process
	Clay Stabilizer Use (yes/no)		X	X		X		318	Yes = 318				No = 0			Clay stabilizer used during the hydraulic fracturing process that can prevent the migration or swelling of clay particles
	Scale Inhibitor Use (yes/no)		X	X		X		318	Yes = 231				No = 87			Scale inhibitor compound was used during the hydraulic fracturing process to prevent formation of scale in the wellbore that may inhibit fluid flow
	Breaker Use (yes/no)		X	X		X		318	Yes = 264				No = 54			Polymer breaking agent was used to reduce viscosity of fluid during the hydraulic fracturing process
	Lift Type (ESP or Gas)		X	X		X		316	ESP = 256				Gas Lift = 62			Indication if either an ESP or Gas lift was used as an artificial lift system in the well
	Azimuth (degrees)	X			X	X		323	163	5	158	162	162	164	231	Orientation of the well derived from the surface and bottom hole longitudes and latitudes
Spatial and Placement Attributes	Surface Hole Latitude (degrees)	X			X	X		318	32.133	0.200	31.585	31.963	32.170	32.305	32.460	Angular distance north or south of the meridian for each well
	Surface Hole Longitude (degrees)	X			X	X		318	-101.759	0.161	-102.047	-101.826	-101.716	-101.659	-101.298	Angular distance on the earth, east or west of the prime meridian at Greenwich, England, to the point on the earth's surface for which the position is being determined
	True Vertical Depth (feet)	X			X	X		318	8,493	620	6,957	8,020	8,418	8,924	10,361	Distance from the surface to the bottom of the well in straight perpendicular line
	Average Bench Spacing (feet)	X			X	X		213	475	389	0	0	600	625	2,387	Distance between the outer most wells in a bench of wells
	Avg. Gamma Ray (API)	X		X		X		143	77	32	7	60	84	99	141	Average gamma ray values. These logs measure the natural emission of gamma rays by a formation. Shales and clays typically possess high natural radioactivity relative to other rock types

Feature Group	Feature	Data Class				Temporal Influence		Descriptive Statistics								Description
		Continuous	Category	Proprietary	Public	Static	Dynamic	Count	Mean	Stdev.	Minimum	25th percentile	50th percentile	75th percentile	Maximum	
	Avg. Resistivity (Ohm-m)	X		X		X		143	662	3,445	5	20	50	147	32,243	Average formation resistivity. These logs measure the resistance of associated rocks to flow of electrical currents. Hydrocarbons do not conduct electricity while all formation waters do and are much less resistive
	Avg. Photoelectric (Pe)	X		X		X		143	3.5	0.9	2.5	3.1	3.4	3.8	12.9	Average photoelectric absorption factor values. The log can infer mineralogy. Sandstones have low Pe, while dolomites, limestones, clays, and heavy and iron-bearing minerals have high Pe
	Avg. Density Porosity (decimal)	X		X		X		143	0.09	0.05	-0.01	0.06	0.08	0.11	0.25	Average density porosity values. The log provides a record of a formation's bulk density. Bulk density is affected by the density of the minerals forming the rock matrix in tandem with the fluid enclosed in the pore spaces. Porosity can, therefore, be inferred from the bulk density
	Avg. Neutron Porosity (decimal)	X		X		X		143	0.14	0.06	0.02	0.10	0.15	0.18	0.31	Average neutron porosity values. The log evaluates the effect of the formation on fast neutrons emitted by a source. Hydrogen common in pore fluids slows captured neutrons substantially. Therefore, the log responds to porosity in the rock matrix
	Stdev. Gamma Ray (API)	X		X		X		143	22	14	0	18	21	27	99	Standard deviation of the gamma ray values for each production zone for a cluster of neighboring wells
	Stdev. Resistivity (Ohm-m)	X		X		X		143	686	2,769	3	18	50	282	24,489	Standard deviation of the formation resistivity values for each production zone for a cluster of neighboring wells
	Stdev. Photoelectric (Pe)	X		X		X		143	0.47	0.23	0.09	0.32	0.42	0.59	1.42	Standard deviation of the photoelectric absorption factor values for each producing zones for a cluster of neighboring wells
	Stdev. Density Porosity (decimal)	X		X		X		143	0.05	0.04	0.01	0.02	0.03	0.05	0.22	Standard deviation of the density porosity values for each producing zones for a cluster of neighboring wells
	Stdev. Neutron Porosity (decimal)	X		X		X		143	0.05	0.04	0.01	0.03	0.04	0.06	0.25	Standard deviation of the neutron porosity values for each producing zones for a cluster of neighboring wells

2.3 Machine Learning Model Development Summary

The ML framework involved developing a deep learning-based model that enables the joint prediction of daily oil (in bbls), water (in bbls), and gas (in Mcf) volumes for unconventional shale wells placed in the Spraberry through Wolfcamp C reservoirs (highlighted orange in Exhibit 2-2). The model uses long short-term memory (LSTM) recurrent neural networks to enable time-series prediction. Model development leveraged Python (version 3) and packages within the Scikit-learn library [43] and Keras. [44] The model was designed to generate production predictions over the entire life of the well. This affords the flexibility to adjust the duration to implement multiple functions which can enable insight (and optimization) to well productivity based on well completion, placement, and operational decisions including extending production forecasts for existing wells and generating production forecasts for new or theoretical wells. The model contains an input feature set spanning 43 attributes with data types that are not commonly available (in large quantities) in the public domain. As noted in Section 2.1, key proprietary input data features include downhole pump inlet pressure, ESP size, detailed well hydraulic fracturing information (i.e., stages, clusters, sand and fluid treatment per stage, average and initial shut-in pressure, and specific chemical additives applied), as well log data of several geologic properties.

2.4 Model Prediction Performance Assessment

The trained model was assessed using a holdout test and validation dataset, as well as against the training data as an additional comparative measure. Root mean squared error (RMSE) and R^2 were used to compare the predicted values from the model against historical production data. RMSE (Equation 1) reflects the error between the predicted value and the ground truth. Smaller RMSE values signify a low error between the predicted value and the ground truth and vice-versa. RMSE is also reflected in the same units of the attribute of interest. R^2 (Equation 2) reflects the degree of correlation between a predicted value and the ground truth. R^2 values range between 0 and 1 and larger values closer to 1 represent minor discrepancies between the ground truth and predicted values.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$ ***Equation 1***

$$R^2 = 1 - \frac{\sum_{i=0}^{n-1}(y_i - \hat{y}_i)^2}{\sum_{i=0}^{n-1}(y_i - \bar{y})^2}$$ ***Equation 2***

where *n* represents the length of the dataset, y_i is the observed value, $\hat{y}_i$ is the simulated or estimated response value, and $\bar{y}$ is the mean value across the observed values.

2.5 Model Performance Summary

As discussed in Section 2.3, the model was used to predict daily oil, water, and gas production from three sets of well data - the training, validation, and test sets (Exhibit 2-1). Exhibit 2-4 displays the model performance in terms of RMSE for the daily volume and the cumulative volumes. The results show low error in the prediction performance, with the lowest prediction error associated with oil production. Additionally, the model demonstrates little variability in the prediction error across predictions of the test, validation, and test sets – the one exception noted to water predictions from the test sets relative to the training and validation sets. A close examination of the water production prediction attributes this issue to two wells in Glasscock County where there was a significant underprediction of water production. These wells were each drilled to depths of just over 7,700 feet—one of which targeted the Lower Spraberry (in northern Glasscock County, Texas) and the other the Wolfcamp A (in central Glasscock County).

Exhibit 2-4. Model performance in RMSE for daily production prediction (left) and cumulative production (right)

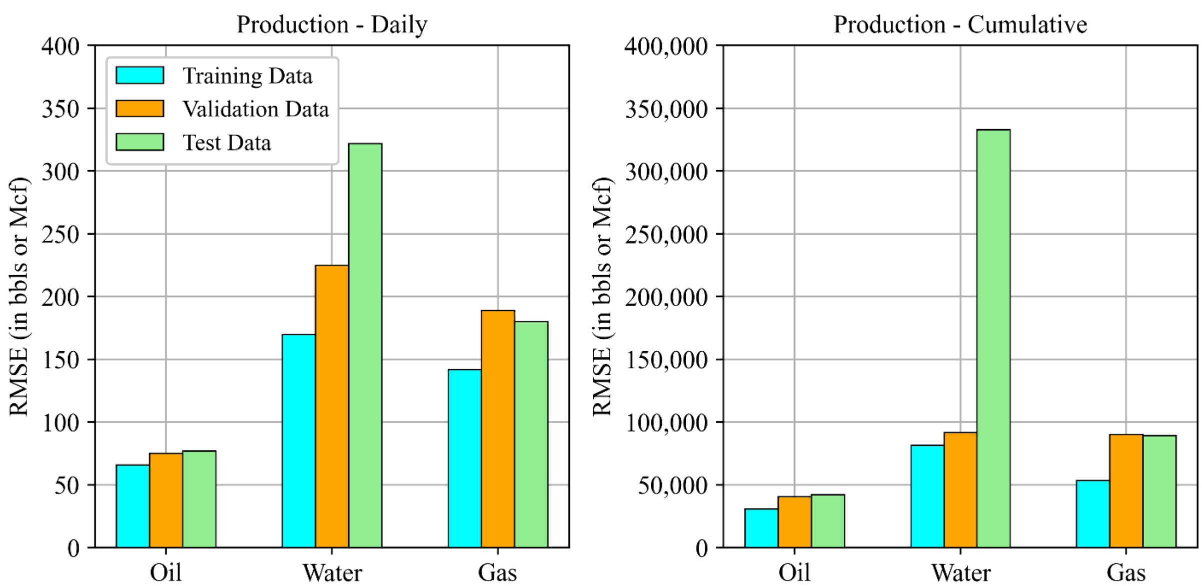
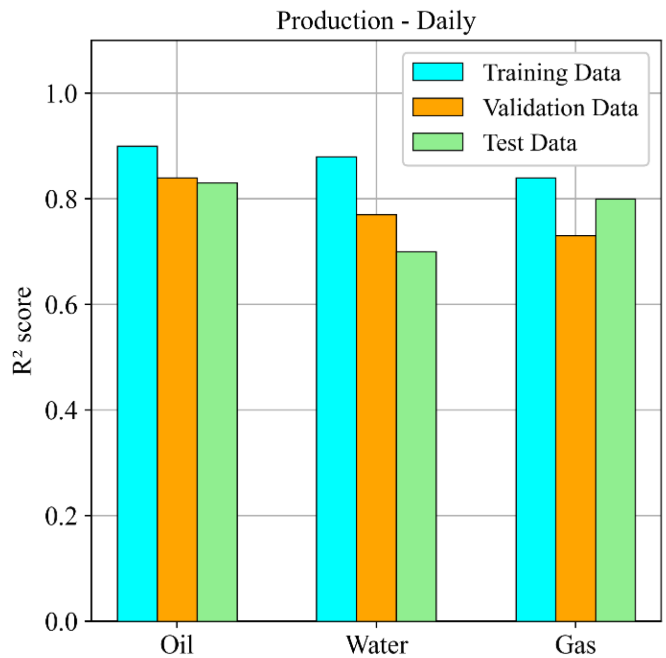


Exhibit 2-5 displays the model performance in terms of R^2 for the daily fluid flows. A similar observation was noted when assessing the model performance in terms of R^2. The model shows the highest prediction performance with daily (and cumulative) oil ($R^2 > 0.8$ on all data sets) relative to the other two fluids. On average (across training, validation, and test datasets), the model is capable of daily prediction accuracy (using R^2 values) over the entire life of a given well on the order of 79 percent for water and gas to upwards of 86 percent (for oil). Overall, the model does well at predicting multiple production outputs at daily resolution. The model also accounts for and gives reasonable predictions in the three production streams when transient well events, such as well shut-ins, occur. [1]

Exhibit 2-5. Model prediction performance in R^2 for daily production prediction

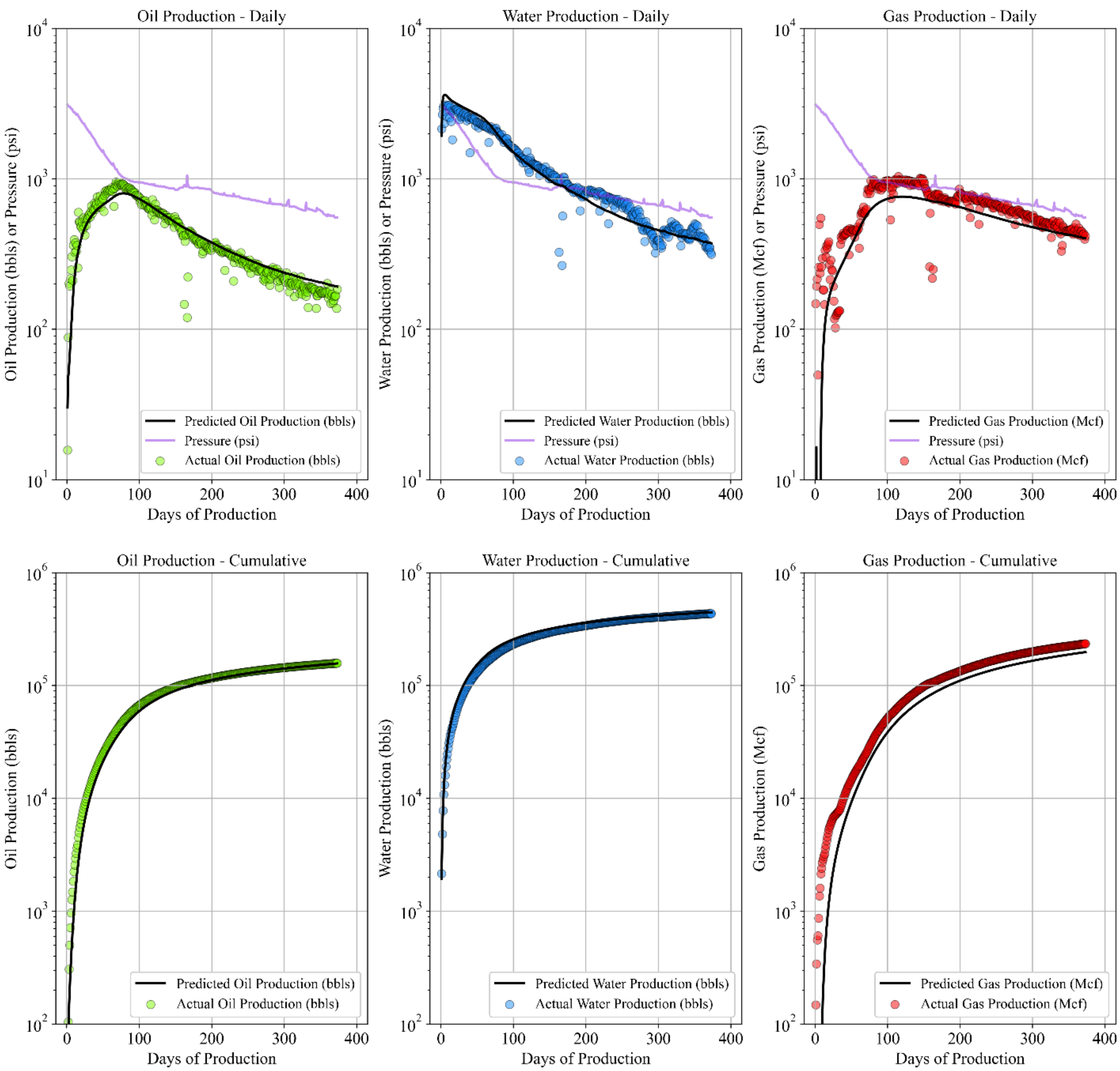


2.6 CASE STUDY WELL

Exhibit 2-6 shows the comparison of empirical field data (including production and noted pump inlet pressure) with the model's predictions for one of the wells in the study test set. The well (highlighted red in Exhibit 2-1) is completed in the Lower Spraberry (in western Howard County, Texas) at a total vertical depth of 7,632 feet and has a perforated interval length of 9,780 ft. This well has experienced relatively uninterrupted production over its life (roughly 380 days). The three-stream fluid production predictions for this well show that the model is exemplary in capturing the daily production trends for all fluid types. Additionally, there is little difference noted in the simulated versus empirical cumulative production. Given that this well has shown largely uninterrupted production and absence of transient events (i.e., spikes or rapid falloffs in either pressure and empirical fluid production) as well as an observed lifespan that provides a combination of a substantial subset of historic data (~ 1 year) and opportunity to forecast near-term production into the future (≤ 5 years), this well was selected for use as the case study.

The historic pressure data that exists for this well which is also largely uninterrupted bodes well for establishing a simple pressure decline model (outlined in Section 2.7) which is ultimately used to generate several pressure management cases used as model input.

Exhibit 2-6. Daily production prediction (top) and cumulative production (bottom) for a relatively uninterrupted well using the joint production prediction model



2.7 Pressure Decline Model and Pressure Drawdown Cases

The analyses in this study utilized a workflow in which the ML model was used to test the production implications of varying the drawdown of the uninterrupted well from the test case (presented in Exhibit 2-6). This workflow involved the creation of different synthetic pressure drawdown cases used as model input. The model was fed these different pressure drawdown cases to generate commensurate oil, water, and gas production outlooks. It is worth noting that of all the model input requirements (listed in detail in Exhibit 3-7 in Vikara et al. [1]), daily pump inlet pressure was the only input set that varied across the pressure drawdown cases evaluated.

All other well performance, well completion, and spatial and placement attribute inputs were fixed across all cases and set at the actual field setting noted for the case study well.

The actual, in-field pressure decline of the well was history matched using a modified Langmuir isotherm equation as expressed in Equation 3 to enable forecasting and pressure drawdown synthetic case creation. The Langmuir isotherm equation was selected to fit the historical data due to its practicality in fitting the pressure-transient nature of the well which is non-linear and hyperbolic. The Langmuir equation has traditionally been used to model experimental data relating to the desorption of oil and gas from shale reservoirs as it relates the absorbed fluid concentration in the shale matrix to the pressure of the reservoir system. [45, 46, 47]

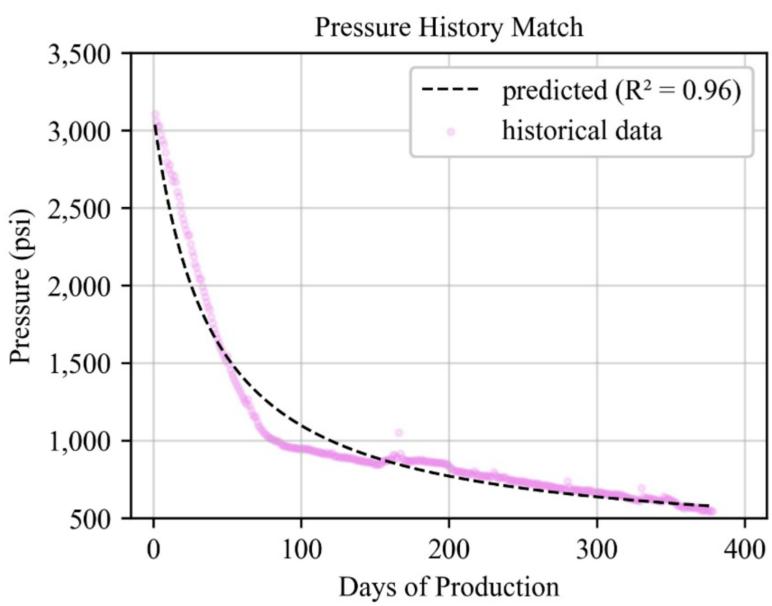
$$P_t = P_i - P_{mult}\left(\frac{Kt}{Kt + c}\right) \qquad \textbf{\textit{Equation 3}}$$

where P_t represents the pressure (psi) at time t days in the well's producing life, P_i is the initial pressure (psi) at time = 0 in the well's producing life, P_{mult} and K are constants, and c is the pressure decline rate.

The R^2 metric as displayed in Equation 2 was used to gage the quality of the history match. The pressure history match is strongly correlated to the observed pressure data from the case study well, with an R^2 value of 0.96 (Exhibit 2-7). Derived values for the pressure decline function in Equation 3 are expressed in Equation 4 below.

$$P_t = P_i - 2788.33\left(\frac{5.39\text{t}}{5.39\text{t} + 209.05}\right) \qquad \textbf{\textit{Equation 4}}$$

Exhibit 2-7. History matched pressure data from the case study well



Five pressure drawdown strategies were generated using Equation 4 by varying the pressure decline rate variable. The pressure decline rate generated during the history-matching process (i.e., c = 209.05) was considered a baseline case. Four additional cases were generated by increasing or decreasing the baseline pressure decline rate by 25% and 50% from the baseline, respectively (Exhibit 2-8). The decreased pressure decline rate cases represent conservative pressure drawdown strategies, while increased pressure decline rate cases represent aggressive drawdown strategies. All cases assume the same starting pressure as well as assume a minimum flowing pressure of 400 psi.

Exhibit 2-8. Pressure decline rates for the modeled drawdown cases

Case	Strategy	Description	Initial Pressure (psi) (P_i)	Pressure Decline Rate (c)
A	Aggressive	50% increase in the drawdown rate	3,107	313.58
B	Aggressive	25% increase in the drawdown rate		261.31
C	Standard	Baseline (drawdown rate modeled from historical data)		209.05
D	Conservative	25% decrease in the drawdown rate		156.79
E	Conservative	50% decrease in the drawdown rate		104.53

3 Pressure Drawdown Case Results

The ML model was used to forecast daily three-stream production data for the varying pressure drawdown cases (specified in Exhibit 2-8) over a five-year producing timeframe for each case. Exhibit 3-1 displays the time-series profiles of the modeled pressure drawdown cases in tandem with the predicted three-stream production outlooks. In general, the aggressive pressure drawdown strategies (A and B) were observed to have the highest oil production rates in the earlier time frames (≤ 45 days production) relative to other cases. The baseline and conservative cases (C, D, and E), however, showed higher oil production rates later in the well's producing life (≥ 90 days of production) and a higher oil production peak. The results show that the timeframe in which the oil production peak occurred across all cases directly corresponds to the pressure decline rate value (*c*) modeled in the cases in Exhibit 2-8.

Model predictions similarly show higher gas production rates in the early times (until approximately 105 producing days) for the aggressive A and B cases as compared to baseline and conservative cases D and E (Exhibit 3-1). After approximately 105 days, gas production peaks corresponding with higher production rates are observed in the baseline and conservative drawdown strategies. In addition, peak oil and gas production rates were highest in case E, decreasing accordingly with increasing pressure decline rates (Exhibit 3-2). The conservative strategies show peak oil and gas occurring rates further into the production timeframe compared to the aggressive cases. Overall, the conservative strategies showed a more sustained duration of higher oil and gas production rates relative to the aggressive drawdown cases – a notion that matches the heuristic understanding of unconventional oil and gas operations. [16, 15, 11, 10, 48]

The model's water production predictions over time showed that the more conservative strategies generated higher water production rates throughout the period explored (Exhibit 3-10) – not only in the later producing timeframes as was witnessed with oil and gas. The lowest pressure decline rate case (Case E) generated the largest volumes of water. However, the most aggressive pressure drawdown case (Case A) had the lowest overall water production rates across the five-year production timeframe. The occurrence of peak water production rates for the cases was noted to occur largely in the same timeframe (near *t* = eight to nine days) of each other (Exhibit 3-2) regardless of the case-by-case trend in water production over the long term.

Exhibit 3-1. Pressure drawdown strategies and the forecasted daily rates for oil, water, and gas over the first five years of production

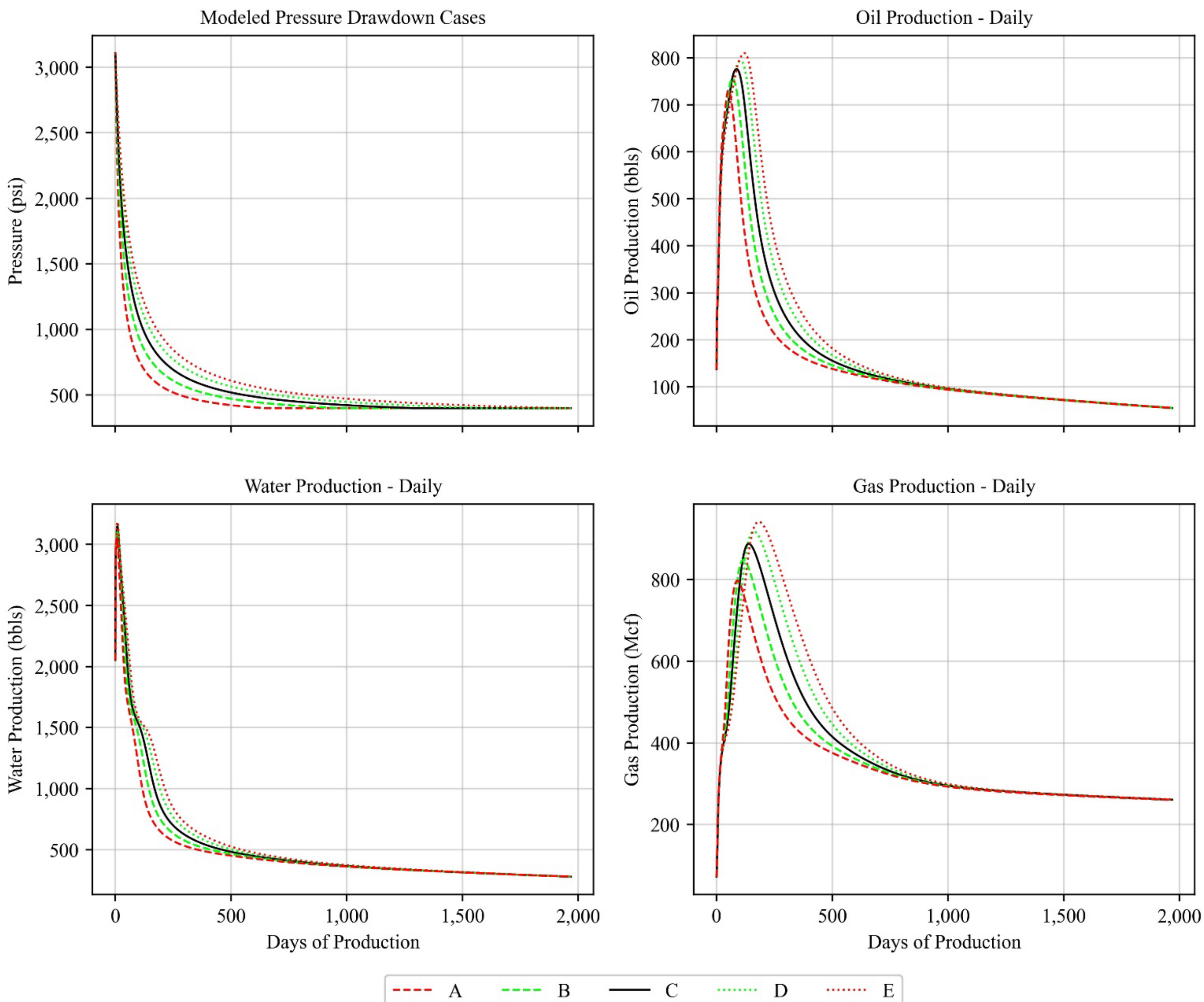
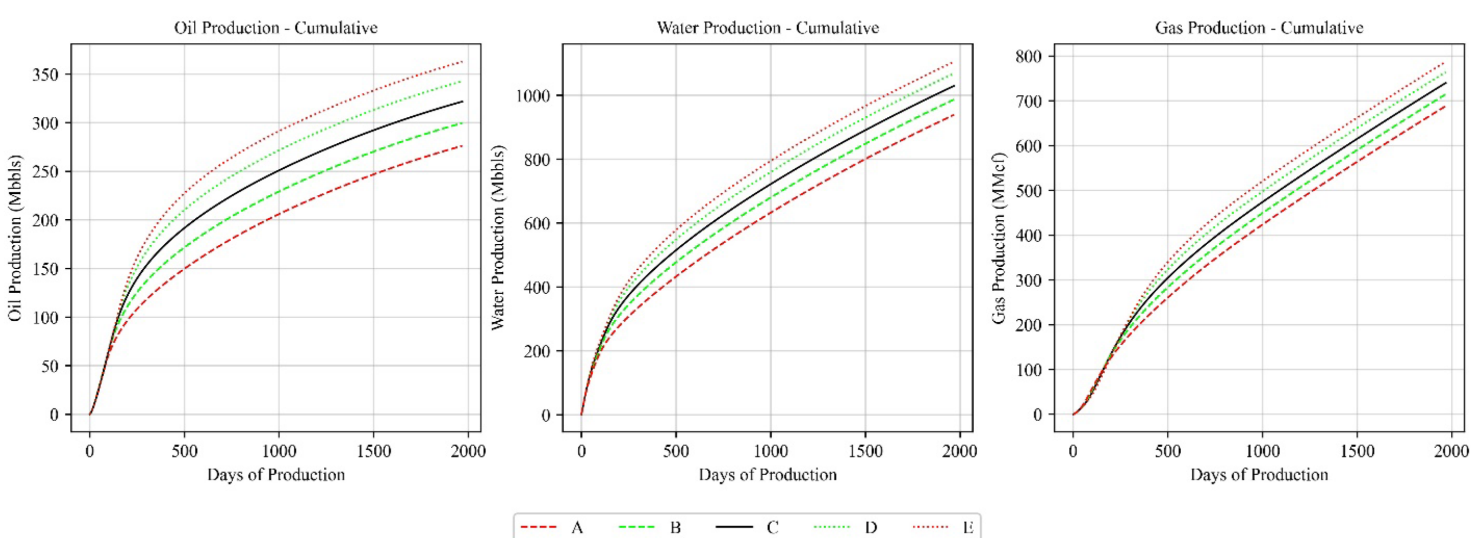


Exhibit 3-2. Peak production time and rate for the modeled pressure drawdown cases

Case	Peak Production Rates (bbls/day or Mcf/day)			Time of Peak Production Rates (days)		
	Oil	Gas	Water	Oil	Gas	Water
A	731	797	3,058	51	90	8
B	756	848	3,116	68	116	8
C	776	888	3,149	86	139	9
D	794	918	3,171	104	161	9
E	810	941	3,186	120	182	9

The cumulative production volume summation (Exhibit 3-3) shows that the more aggressive pressure drawdown cases generate more oil and gas production in the short term (90 to 180 days of production), however, rates diminish quickly shortly after. In general, conservative cases D and E provide the highest cumulative volumes of oil, gas, and water relative to all other cases – even despite the later emergence of peak production for oil and gas. Cumulative production data from the different cases are compared relative to baseline case C (Exhibit 3-3), which closely reflects the infield pressure drawdown for the case study well. Analysis of cumulative production data shows that aggressive drawdown strategies offer an increase of 1.89% to 4.47% in oil production at 30 days and a 2.03% to 3.72% increase in oil production at 60 days relative to the baseline (Exhibit 3-4). The relative difference in cumulative oil production for the aggressive drawdown cases reduces between 0.22% and -3.37% of the baseline case C at 90 days of production. This difference extends even more so after one year of production to between -10.74% and -22.83% and then between -7.03% and -14.52% after five years of production (Exhibit 3-4). Similar trends are observed in gas production with aggressive pressure drawdown strategies showing a difference as high as 8.49% to 18.94% relative to the baseline at 180 days of production, before reducing to -3.59% to -7.33% from the baseline at five years of production (Exhibit 3-5). It is worth noting that despite the larger cumulative fluid volumes produced under the conservative drawdown cases, these cases yield comparatively lower oil and gas recovery in the short-term production (approximately 90 days for oil and 180 days for gas production) and comparatively higher oil and gas recovery in the medium term. Cumulative oil production was noted to be as low as -1.24% to -2.59% from the baseline at 90 days before increasing to 6.68% and 13.06% more than the baseline at five years for the conservative drawdown strategies. Cumulative gas production was noted to be as low as -5.76% to -9.50% from the baseline at 90 days before increasing to 3.44% and 6.73% more than the baseline at five years for the conservative drawdown strategies (Exhibit 3-5). Cumulative water production prediction data demonstrate a much different trend compared to oil and gas – where Cases D and E consistently produce more water than all other cases at every point in time (Exhibit 3-6).

Exhibit 3-3. Pressure drawdown strategies and the cumulative production outlook for oil, water, and gas over the first 5 years



The modeling results suggest that more aggressive pressure drawdowns may be advantageous for initial production by providing more oil early on. However, the aggressive cases also result in higher early associated gas production and do not sustain oil production at rates shown in more conservative cases over the long term. From an economic point of view, greater production of oil can potentially offer a larger revenue stream but the handling of associated gas and water (depending on what they can be used for or how they are disposed of) can have a substantial cost and/or environmental impacts. One of the more favorable tradeoffs observed is that more aggressive drawdown approaches yield marginally lower water production – a result that would lower a given project's cost for water treatment and/or disposal to some degree. This will potentially increase the profitability of the well. Plus, it has been noted that the injection of large volumes of wastewater from O&G operations is strongly correlated to the increased frequency of occurrence of induced seismic events. [49]

Exhibit 3-4. Comparison of cumulative oil production for the different pressure drawdown strategies over 30 days, 60 days, 90 days, 1 year, and 5 years of production

Case	Cumulative Oil Production (Mbbls/day)						Incremental Daily Oil Production Difference Relative to Case C (%)					
	30 Days	60 Days	90 Days	180 Days	1 Year	5 Years	30 Days	60 Days	90 Days	180 Days	1 Year	5 Years
A	14.96	36.26	55.97	91.50	129.60	268.09	4.47	3.72	-3.37	-20.04	-22.83	-14.52
B	14.59	35.67	58.05	104.75	149.91	291.57	1.89	2.03	0.22	-8.46	-10.74	-7.03
C	14.32	34.96	57.92	114.43	167.95	313.63	Baseline					
D	14.13	34.41	57.20	121.12	184.06	334.58	-1.33	-1.57	-1.24	5.85	9.59	6.68
E	13.98	33.96	56.42	125.32	198.38	354.60	-2.37	-2.86	-2.59	9.52	18.12	13.06

Exhibit 3-5. Comparison of cumulative gas production for the different pressure drawdown strategies over 30 days, 60 days, 90 days, 1 year, and 5 years of production

Case	Cumulative Gas Production (MMcf/day)						Incremental Daily Gas Production Difference Relative to Case C (%)					
	30 Days	60 Days	90 Days	180 Days	1 Year	5 Years	30 Days	60 Days	90 Days	180 Days	1 Year	5 Years
A	9.49	26.64	49.73	114.54	207.22	651.02	3.38	17.20	18.94	-3.46	-14.57	-7.33
B	9.26	23.96	45.36	118.68	226.53	677.29	0.87	5.41	8.49	0.03	-6.61	-3.59
C	9.18	22.73	41.81	118.65	242.56	702.54	Baseline					
D	9.13	22.18	39.40	116.04	255.02	726.70	-0.54	-2.42	-5.76	-2.20	5.14	3.44
E	9.10	21.88	37.84	111.99	263.87	749.83	-0.87	-3.74	-9.50	-5.61	8.79	6.73

Exhibit 3-6. Comparison of cumulative water production for the different pressure drawdown strategies over 30 days, 60 days, 90 days, 1 year, and 5 years of production

Case	Cumulative Water Production (Mbbl/day)						Incremental Daily Water Production Difference Relative to Case C (%)					
	30 Days	60 Days	90 Days	180 Days	1 Year	5 Years	30 Days	60 Days	90 Days	180 Days	1 Year	5 Years
A	84.68	140.10	184.44	265.71	369.62	898.69	-5.47	-9.67	-10.07	-16.88	-17.15	-9.14
B	87.86	148.71	196.82	296.74	411.35	946.44	-1.92	-4.12	-4.04	-7.17	-7.80	-4.32
C	89.58	155.10	205.10	319.66	446.14	989.13	Baseline					
D	90.68	159.80	211.81	336.58	475.85	1,028.30	1.23	3.03	3.27	5.29	6.66	3.96
E	91.46	163.20	217.55	348.85	501.64	1,064.82	2.10	5.23	6.07	9.13	12.44	7.65

4 CONCLUSIONS

The advancement in DA and ML affords a multitude of opportunities for O&G operators to apply these types of data-driven techniques toward improving reservoir management and operational decisions. The ML-based model employed in this study was purposely implemented to explore its utility to evaluate the impact of varying drawdown strategies on production for one case study well in the Permian Basin. The study findings largely support that the application of the deep learning-based, three-stream predictive model developed under the Vikara et al. study [1] can offer utility in evaluating the effect of pressure drawdown strategies on total hydrocarbon and water production from shale reservoirs. The three stream fluid predictions resulting from the various pressure management cases evaluated within the study largely trend with notional expectations of unconventional O&G operations undergoing either rapid or more sustained pressure management strategies. Results demonstrate that aggressive and rapid drawdown cases tend to provide earlier peak oil and gas production relative to the more sustained pressure management cases. However, the more sustained pressure cases produce larger cumulative volumes of oil and gas (and water) overall.

The deep learning-based model used for this study was found to accurately replicate and forecast production from unconventional reservoirs in the Permian Basin when developed with a mix of well performance, completion, and well placement attributes as inputs. [1] While the production outlooks generated in this study appear to suggest that the model's response to dynamic pressure data matches the heuristic understanding of unconventional oil and gas operations, validating model predictions is still needed. This notable limitation may warrant further exploration through field testing and validation (and potentially calibration) of ML-based model performance. It is also worth noting that the model leans heavily on data that is largely held propriety by O&G operations – therefore, adapting the model for application to other regions of interest would require procuring the needed data for transferability.

Given that advanced computational resources are becoming more widely available and digital formats of O&G data are becoming the norm, ML and DA are slated to provide unique and valuable compliments to existing approaches for O&G operational decision support. [18, 50] The model applied in this study was used to explore one specific aspect of unconventional O&G operations. However, the model itself was originally developed to evaluate and appraise the impact of various types of data (those considered proprietary vs. data more publicly available) on model response using three-stream production in unconventional wells as a modeling focus. As a result, these ML-based models, while typically built to be fit for purpose, afford the ability to be modified to address additional objectives (an aspect of transfer learning). Therefore, the model, or variants like it, could be utilized to more utility in future endeavors moving forward. For instance, this sort of rapid and accurate prediction model employed in this study can be leveraged to help assess the multitude of completion, design, and production implications associated with unconventional O&G operations. Additionally, ML models of this nature can be advantageous for O&G operators in evaluating drawdown strategies aimed to optimize project economics, especially given the volatile nature of O&G markets and commodity prices. They can also be used to explore the effect of alternative well design decisions on production, including hydraulic fracture completion parameters. It has been noted that significant environmental concerns exist associated with shale O&G development including water usage, induced seismicity correlation with wastewater disposal through subsurface injection, and flaring (and possible venting) of produced natural gas. This study's model output can directly provide the needed insight to support the formulation of management and/or remedial strategies based on the volumes of fluids expected from unconventional O&G development operational conditions.

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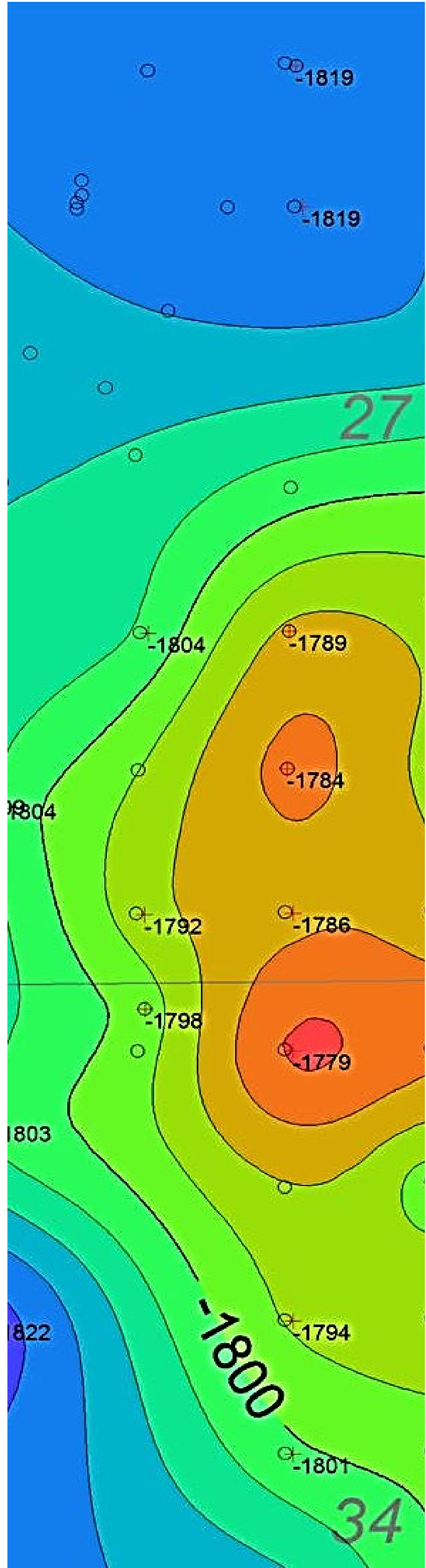

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