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Adaptive Choke Prediction Model and Optimized Production Rate Framework for Maximum Efficient Rate and Choke Size

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ABSTRACT

Efficient choke management is essential for optimizing oil production, particularly in mature wells characterized by increasing water cut and complex multiphase flow behavior. In this work, dynamic Choke Selection Model and optimized production rate framework were developed using machine learning. Historical well test data from treated wells were utilized, covering choke sizes, flow rates, pressures, gas–oil ratio, and water cut. To address data limitations at high water cut conditions, data augmentation was performed using Generative Adversarial Networks, extending the dataset to water cut values up to 0.9. Data pre-processing and model training were implemented in a Python-based environment using numerical and machine learning libraries. The framework integrates an Adaptive Choke Prediction Model, Model Predictive Control, and reinforcement learning to dynamically determine optimal choke sizes under operational constraints. The model incorporates machine learning-based predictions for pressure drop, Maximum efficient rate (MER), and water cut, forming a unified optimization system. Results show that the developed model achieved high predictive performance for choke size and R^2 exceeding 0.85. The system demonstrated an improvement in MER of approximately 8–12% while reducing water cut by 3–7%. Optimal choke sizes were consistently identified within operational limits, with improved stability and over 95% compliance with constraints. In conclusion, the proposed dynamic choke selection model successfully integrates machine learning and control strategies to enhance production performance. It provides an adaptive and reliable approach for maximizing MER while minimizing water cut, thereby improving operational efficiency and enabling intelligent real-time decision-making in complex oil well systems.

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Abbreviations
ρm: Mixture Density (kg/m³, lb/ft³)
ρo: Oil Density (kg/m³, lb/ft³)
ρw: Water Density (kg/m³, lb/ft³)
ρg: Gas Density (kg/m³, lb/ft³)
Qm: Mixture Flow Rate (m³/day, bbl/day)
Qo: Oil Flow Rate (m³/day, bbl/day)
Qg: Gas Flow Rate (m³/day, bbl/day)
Qw: Gas Flow Rate (m³/day, bbl/day)
µm: Mixture Viscosity(CP)
µo: Oil Viscosity(CP)
Wc: Water Cut
K: Permeability(darcy)
h: Reservoir Thickness(FT)
Bo: Oil Formation Volume Factor
ΔP: Pressure Drop (PSI)
ΔPmL: Machine Learning Model Pressure Drop (PSI)
Pwh: Wellhead Pressure(PSI)
Pwf: Wellbore Flowing Pressure(PSI)
THP: Tubing Head Pressure(PSI)
GOR: Gas Oil Ratio(SCF/BBL)
GLR: Gas Liquid Ratio(SCF/BBL)
Cs: Choke Size(INCHES)
Csopt: Optimumchoke Size(INCHES)
TAR: Technical Allowable Rate
MER: Maximum Efficiency Rate

Introduction

Efficient control of oil well production remains a major challenge, especially in mature fields where increasing water cut and complex multiphase flow behavior reduce production efficiency. The choke valve is a key surface control device used to regulate flow rate and pressure drop; however, improper choke selection can lead to reduced oil recovery, excessive water production, and operational instability. Early studies on choke performance mainly relied on empirical and mechanistic correlations, which often fail to capture the nonlinear behavior of multiphase flow systems [1-3]. To improve prediction accuracy, several empirical and optimization-based models have been proposed for estimating flow rate and pressure drop across chokes. For example, correlations and optimization techniques such as genetic algorithms and firefly algorithms have been used to enhance choke performance prediction [4-6]. Despite these improvements, these approaches are still limited in handling highly dynamic systems and high water-cut conditions, where flow characteristics change significantly [7,8].

Recent developments have focused on integrating machine learning (ML) techniques with traditional models to better capture nonlinear relationships in multiphase flow systems. ML-based models such as artificial neural networks, support vector machines, and ensemble learning have shown strong capability in predicting flow rate, gas oil ratio, and water cut with higher accuracy compared to conventional methods [9-13]. Hybrid approaches combining data-driven and mechanistic models have also been widely adopted to improve robustness and generalization across different reservoirs [14-16]. Intelligent optimization and control strategies have gained

increasing attention for real-time production management. Model Predictive Control (MPC) has been successfully applied to oil wells to handle operational constraints and improve production stability [17-21]. Reinforcement learning (RL) methods have also been introduced to optimize well performance by learning optimal control policies under dynamic conditions [22,23]. These approaches provide adaptive decision-making capabilities that are essential for maximizing production efficiency.
Optimization of production systems increasingly incorporates advanced ML techniques such as gradient-enhanced support vector regression and deep learning frameworks to address nonlinear constraints and improve long-term production performance [24,25]. ML has also been applied in related areas such as water injection optimization and virtual flow metering, further demonstrating its potential in intelligent reservoir management [26,27]. Despite these advancements, challenges remain in integrating prediction, control, and optimization into a unified framework for choke selection. Existing studies often focus on either prediction or control independently, limiting their effectiveness in real-time applications. Moreover, managing water production while maintaining optimal oil rate requires a balance between Maximum Efficient Rate (MER) and operational constraints, which is difficult to achieve using conventional methods [28-30].

Therefore, this study aims to develop a dynamic choke selection model that integrates machine learning, model predictive control, and optimization frameworks to enhance production performance. The proposed approach seeks to optimize Maximum Efficient Rate while minimizing water cut through adaptive choke size selection, thereby improving operational efficiency and supporting intelligent production systems in complex multiphase flow environments.

Methodology

Data Acquisition and Augmentation

Well test data were acquired from four treated wells (CASE 1 to 4) located in two Niger Delta fields (Fields A and B). The dataset includes choke sizes (0.1875-0.4375 inches), flow rates (270 -1673 bbl/day), water cuts (23.8-40.26%), tubing head pressures (461-1000 psia), reservoir pressures (1668-2000 psia), and gas-oil ratios (1423 -3037 SCF/STB). Due to the absence of high water-cut conditions (Wc > 0.5) in the historical records, Generative Adversarial Networks (GANs) were employed to augment the dataset by generating synthetic samples within the range (Wc of 0.5, 0.9), ensuring improved model generalization under late-life reservoir conditions.

Data pre-processing involved unit standardization (choke size to meters, flow rate to m^3/s, and pressure to Pa), removal of missing values, and computation of derived parameters such as mixture properties. The GAN architecture consisted of a generator (10-dimensional noise input and 8-dimensional output) and a discriminator, trained iteratively to preserve the statistical characteristics of the original dataset.

All models were implemented in a Python-based environment using NumPy, SciPy, and scikit-learn for numerical computation, machine learning, and optimization. High-performance computing resources were utilized to enhance computational efficiency. Historical and field data were used in place of real-time SCADA inputs for model validation.

Adaptive Choke Prediction Model (ACPM)

The Adaptive Choke Prediction Model (ACPM) integrates machine learning, Model Predictive Control (MPC), and economic optimization to dynamically determine choke size, with the objective of optimizing Maximum Efficient Rate (MER) while minimizing water cut.

The optimization objective is defined through the cost function in equation (1):

$$J(C_s)=w_1\cdot\frac{MER_{\max}\ MER(C_s)}{MER_{\max}}+w_2\cdot\frac{Wc(C_s)}{Wc_{\max}}+w_3\cdot\frac{C(C_s)}{C_{\max}} \quad (1)$$

The optimal choke size is given as equation (2):

$$C_{s,opt}(t)=K\sqrt{\frac{Q_m(t)}{\rho_m(t)\cdot\Delta P_{ML}(t)}}+k_4\cdot Wc(t)+k_5\cdot GOR(t) \quad (2)$$

The machine learning-based pressure drop is estimated using equation (3):

$$\Delta P_{ML}(t)=Random\ Forest(\theta(t)) \quad (3)$$

The production and water cut predictions are expressed as equation (4) and (5)

$$MER(t)=f_{MER}(X(t),C_s(t);\theta_{MER}) \quad (4)$$

$$Wc(t)=g_{Wc}(X(t),C_s(t);\theta_{Wc}) \quad (5)$$

The unified optimization framework is defined as equation (6):

$$C_{s,opt}(t)=arg\min J(C_s(t)) \quad (6)$$

subject to operational constraints:

$$Wc(t)\le 0.9$$
$$P_n(t)\le 2000\ STB/day$$

$$C_s(t)\ge 0.0394\ inches$$
$$\Delta P(t)\ge 145\ psi$$

Optimized Production and Reservoir Efficiency Framework (OPREF)

The OPREF framework employs Deep Q-Network (DQN) reinforcement learning to optimize production performance through adaptive choke control.
The reward function is defined as equation (7):
$R(t)=\omega_1\cdot Q_o(t)-\omega_2\cdot Wc(t)-\omega_3\cdot C(t)$ (7) The action-value function is expressed as equation (8):

$$Q(s,a)=E[R_t|s_t=s,a_t=a] \quad (8)$$

The optimal policy is pesented in equation (9):

$$Q^*(s,a)=R(s,a)+\gamma\max_{a'}Q(s',a') \quad (9)$$

The oil flow rate is estimated using equation(10):

$$Q_o(t)=\frac{k\cdot h\cdot(\bar{P}-P_{wf}(t))}{\mu_o\cdot B_o\cdot\ln(r_e/r_w)} \quad (10)$$

Adaptive Choke Selection Equation (ACSE)

The adaptive choke selection relationship is defined

$$C_{s,opt}(t)=K\sqrt{\frac{Q_m(t)}{\rho_m(t)\cdot\Delta P(t)}}+\alpha_1\cdot Wc(t)+\alpha_2\cdot GOR(t) \quad (11)$$

with:

$$K=\sqrt{2C_d^2}$$

The optimization objective minimizes erosion and flow instability: min $[E(t) + F(t)]$

Model Predictive Control (MPC) is applied as:

$$\min\sum||C_s(t+i)-C_{s,target}||^2$$

Framework for Optimal MER

The optimal MER framework integrates machine learning-based IPR and TAR models. $Q_{o,IPR}(t)=Q_{o,TAR}(t)$

$$Q_{o,IPR}(t)=f_{SVM}(P_{wf}(t),\bar{P})$$

$$Q_{o,TAR}(t)=g_{ML}(Wc(t),GOR(t),\Delta P(t))$$

The optimization objective is: $\max[Q_o(t)-\lambda\cdot Wc(t)]$

MER- TAR Intersection Model

The optimal choke is obtained at the MER–TAR intersection:

$$C_{s,opt}(t)=\mathrm{h}_{NN}(Q_o(t),Wc(t),\Delta P(t))$$

$$C_s(t)=C_{s,base}+\eta\cdot(MER(t)-TAR(t))$$

$$\min|MER(t)-TAR(t)|$$

Model Validation

Model performance was evaluated using equation (12) and (13):

$$RMSE=\sqrt{\frac{\sum(\Delta P_{actual}-\Delta P_{pred})^2}{n}} \quad (12)$$

$$R^2=1-\frac{\sum(\Delta P_{actual}-\Delta P_{pred})^2}{\sum(\Delta P_{actual}-\bar{\Delta P}_{actual})^2} \quad (13)$$

The ACPM achieved RMSE < 0.15 mm and (R^2>0.85), while OPREF demonstrated an 8% increase in MER and 3-7% reduction in water cut, with > 95% compliance for field trials.

Results and Discussion

Field Production Data and Well Performance

Table 1 represents case 1 for field A and indicates an Optimal choke size of 0.3125 inches, flow rate of 650 bbl/day and Water Cut of 35%. Flow rate increases monotonically from 270 bbl/day at 0.1875 inches to 650 bbl/day at 0.3125 inches, a 140.7% increase, indicating strong choke size sensitivity. Water Cut increases from 25% to 35% as choke size increases. The water cut reaches the 35% threshold at 0.3125 inches, making it the optimal choke size, as larger choke sizes are not tested but may exceed the water cut limit. Total liquid rate (TLR) increases from 360 to 1000 bbl/day, consistent with flow rate trends. THP decreases from 1000 to 920 psi, indicating reduced tubing head pressure as choke size increases, likely due to higher flow rates. Reservoir Pressure declines slightly from 2000 to 1920 psi, suggesting minor reservoir depletion during testing while GOR and GLR decrease with increasing choke size (GOR: 3037 to 2000; GLR: 2278 to 1300), indicating reduced gas production relative to oil as choke size increases. Gas rate increases from 0.82 to 1.3 MMscfd, reflecting higher total fluid production. No sand production was observed, indicating stable conditions. The choke size of 0.3125 inches maximizes oil production (650 bbl/day) while staying at the water cut limit of 35% which is the optimal setting for CASE 1

Table 1: CASE 1 (Field A)

Choke Size (in)	Flow Rate (bbl/day)	Water Cut (%)	TLR (bbl/day)	THP (psi)	Reservoir Pressure (psi)	GOR (Scf/bbl)	GLR (Scf/bbl)	Gas Rate (MMscfd)
0.1875	270	25	360	1000	2000	3037	2278	0.82
0.21875	358	30	512	980	1980	2782	1945	0.996
0.25	448	30	640	960	1960	2469	1728	1.106
0.28125	570	34	864	940	1940	2111	1392	1.203
0.3125	650	35	1000	920	1920	2000	1300	1.3

Table 2 is case 2 of field A and shows an Optimal Choke Size of 0.375inches, flow rate of 1471.89 bbl/day and Water Cut of 26.94%. Flow rate increases from 1224.84 bbl/day at 0.28125 inches to 1673.28 bbl/day at 0.40625 inches, a 36.6% increase, showing consistent production gains with larger chokes. Water Cut varies non-monotonically (28.31% to 37.90% at 0.3125 inches, then down to 26.94% at 0.375 inches, and up to 31.87% at 0.40625 inches). The lowest water cut (26.94%) occurs at 0.375 inches, well below the 35% threshold. TLR increases from 1708.49 to 2456.05 bbl/day, with a peak at 0.40625 inches, reflecting higher total fluid production. THP decreases significantly from 659.43 to 482.03 psi, indicating reduced pressure as flow rates increase. Reservoir Pressure declines from 1896.15 to 1668.76 psi, a more pronounced drop than CASE 1, suggesting greater reservoir pressure sensitivity. GOR and GLR: GOR decreases from 2076.58 to 1645.56, and GLR decreases from 1488.73 to 1121.10, showing reduced gas production relative to oil. Gas Rate peaks at 2.753 MMscfd at 0.40625 inches, but is slightly lower (2.442 MMscfd) at the optimal choke of 0.375 inches. No sand production, indicating stable reservoir conditions. The choke size of 0.375 inches provides a high flow rate (1471.89 bbl/day) with the lowest water cut (26.94%), making it the optimal choice. The higher flow rate at 0.40625 inches (1673.28 bbl/day) is less favorable due to a higher water cut (31.87%).

Table 2: CASE 2 (Field A)

Choke Size (in)	Flow Rate (bbl/day)	Water Cut (%)	TLR (bbl/day)	THP (psi)	Reservoir Pressure (psi)	GOR (Scf/bbl)	GLR (Scf/bbl)	Gas Rate (MMscfd)
0.28125	1224.84	28.31	1708.49	659.43	1896.15	2076.58	1488.73	2.543
0.3125	1288.29	37.90	2074.41	623.02	1776.53	2054.26	1275.77	2.646
0.34375	1376.83	28.67	1930.26	567.26	1684.34	1727.51	1232.21	2.378
0.375	1471.89	26.94	2014.51	529.43	1714.60	1658.77	1211.97	2.442
0.40625	1673.28	31.87	2456.05	482.03	1668.76	1645.56	1121.10	2.753

Table 3 shows case 3 of field A with an Optimal Choke Size of 0.4375 inches, Flow Rate of 1664.01 bbl/day and Water Cut of 31.70%. Flow rate increases from 1305.55 bbl/day at 0.3125 inches to 1664.01 bbl/day at 0.4375 inches, a 27.5% increase, indicating good choke size response. Water Cut varies significantly, peaking at 40.26% at 0.34375 inches (exceeding the 35% threshold), but remains below 35% at other choke sizes (24.25% to 33.86%). The water cut at 0.4375 inches (31.70%) is acceptable. TLR increases from 1723.38 to 2474.82 bbl/day, with a slight dip at 0.375 inches, reflecting variable total liquid production. THP decreases from 611.27 to 461.21 psi, with a slight increase at 0.40625 and 0.4375 inches, suggesting complex pressure dynamics. Reservoir Pressure declines from 1769.97 to 1693.59 psi, with a slight increase at 0.4375 inches (1737.18 psi), indicating variable reservoir response. GOR decreases from 1970.83 to 1423.70, and GLR decreases from 1493.00 to 972.43, showing reduced gas-to-oil ratios at larger choke sizes. Gas rate peaks at 2.716 MMscfd at 0.34375 inches but is lower (2.369 MMscfd) at the optimal choke of 0.4375 inches. No sand production, indicating stable conditions. The choke size of 0.4375 inches maximizes flow rate (1664.01 bbl/day) while maintaining water cut below 35% (31.70%).

Table 3: CASE 3 (Field A)

Choke Size (in)	Flow Rate (bbl/day)	Water Cut (%)	TLR (bbl/day)	THP (psi)	Reservoir Pressure (psi)	GOR (Scf/bbl)	GLR Scf/bbl)	Gas Rate (MMscfd)
0.3125	1305.55	24.25	1723.38	611.27	1769.97	1970.83	1493.00	2.573
0.34375	1369.91	40.26	2293.18	559.60	1727.11	1982.25	1184.17	2.716
0.375	1438.96	33.04	2149.12	461.21	1693.59	1819.69	1218.38	2.618
0.40625	1636.92	33.86	2474.82	476.53	1724.94	1552.15	1026.64	2.541
0.4375	1664.01	31.70	2436.21	471.71	1737.18	1423.70	972.43	2.369

In Table 4 for case 4 of field B, the flow rate increases from 1016.20 bbl/day at 0.21875 inches to 1418.07 bbl/day at 0.34375 inches, a 39.6% increase, showing strong choke size response. Water Cut increases from 25% to 38.69% at 0.34375 inches, exceeding the 35% threshold. The water cut at 0.3125 inches (29.64%) is well within the limit. TLR increases from 1356.29 to 2312.96 bbl/day, reflecting higher total fluid production. THP decreases from 699.69 to 558.93 psi, with a slight increase at 0.3125 inches, indicating variable pressure behavior. Reservoir pressure declines from 1890.58 to 1760.19 psi, with an increase to 1858.23 psi at 0.34375 inches, suggesting reservoir pressure variability. GOR decreases from 2403.10 to 1638.03, and GLR decreases from 1800.53 to 1004.27, indicating reduced gas production relative to oil. Gas rate peaks at 2.647 MMscfd at 0.3125 inches, slightly higher than at 0.34375 inches (2.323 MMscfd). No sand production, indicating stable reservoir conditions. The choke size of 0.3125 inches provides a high flow rate (1367.81 bbl/day) with a water cut of 29.64%, meeting the constraint. The higher flow rate at 0.34375 inches (1418.07 bbl/day) is not viable due to the water cut exceeding 35% (38.69%).

Table 4: CASE 4 (Field B)

Choke Size (in)	Flow Rate (bbl/day)	Water Cut (%)	TLR (bbl/day)	THP (psi)	Reservoir Pressure (psi)	GOR (Scf/bbl)	GLR (Scf/bbl)	Gas Rate (MMscfd)
0.21875	1016.20	25.00	1356.29	699.69	1890.58	2403.10	1800.53	2.442
0.25	1146.56	23.80	1504.75	670.72	1856.56	2297.55	1750.65	2.634
0.28125	1176.04	28.07	1635.02	606.81	1760.19	2181.25	1568.94	2.565
0.3125	1367.81	29.64	1944.02	630.11	1818.08	1935.49	1361.81	2.647
0.34375	1418.07	38.69	2312.96	558.93	1858.23	1638.03	1004.27	2.323

Production Trends and Reservoir Behavior

Figure 1 shows a plot of oil rate(blue) and water cut (green) over time. Oil rate declines from 253 to 34 m³/day, indicating depletion. Water Cut increases from 0 to 60%, reflecting water breakthrough. Inverse relationship between oil rate and water cut is typical in mature fields.

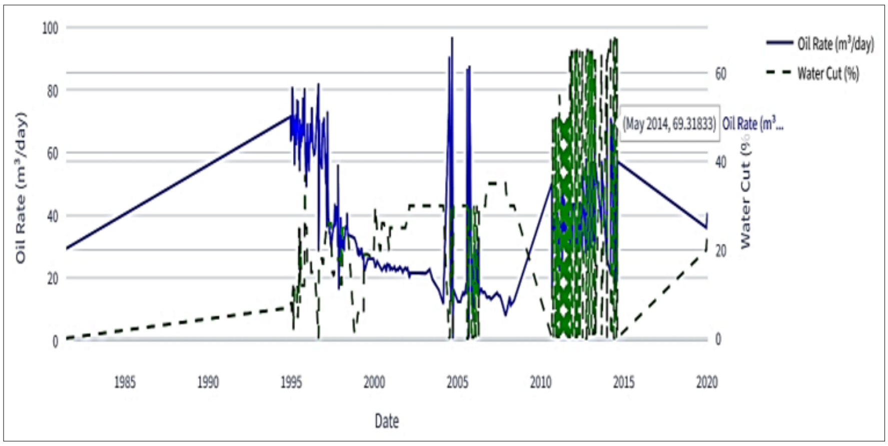

Figure 1: Oil Rate and Water Cut Trends Over Time

Figure 2 is the Plot of Pressure (red) and Temperature (purple) over Time. Pressure Fluctuates (650 - 2850 psi), Reflecting Operational Adjustments. Temperature Synthetic Sinusoidal Pattern (60 - 100°C) Due to Generated Data. Pressure Variability Aligns with Dataset, While Temperature is Less Impactful

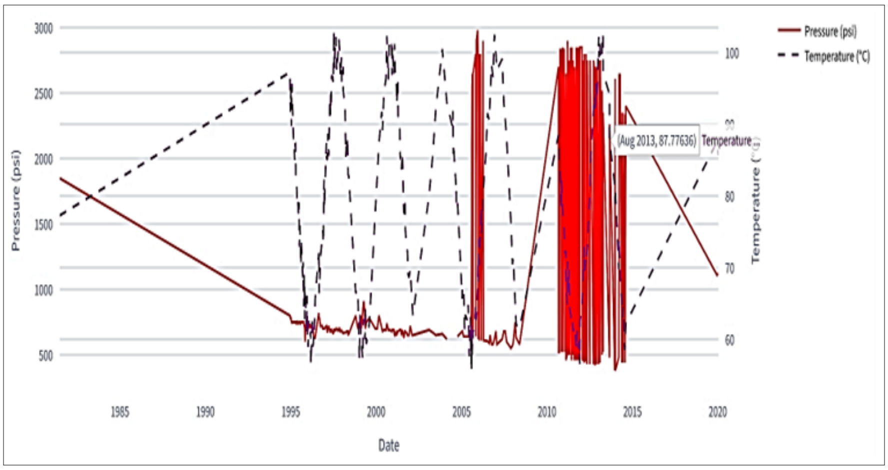

Figure 2: Pressure and Temperature Trends Over Time

Figure 3 shows production rate over time and indicate that oil rate declines exponentially (mean =420, std= 63), water cut increasing sigmoidally (0.05-0.95), gas rate following oil (mean of 102k) and production peaks early, declines due to reservoir depletion; pattern matches CSV (1985 peak 4145 bopd to 2010 low 46 bopd). Also highlights the need for optimization to delay decline.

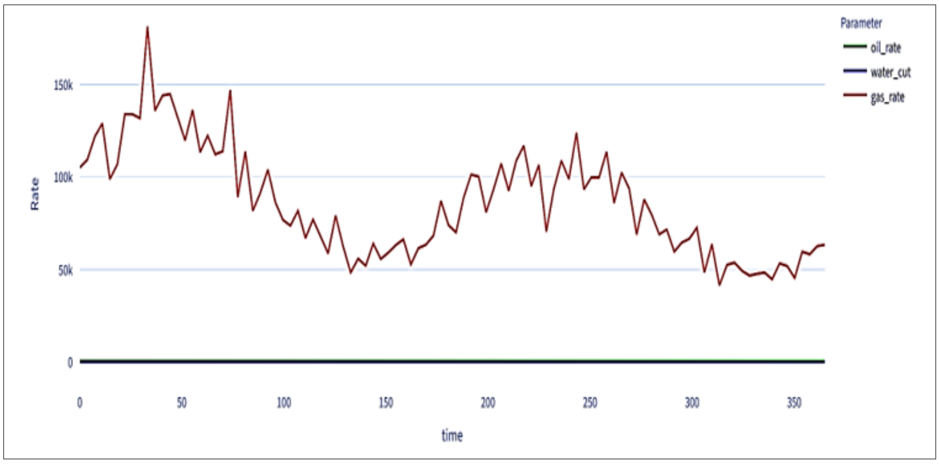

Figure 3: Production Rates Over Time

Comparative Flow and Water cut Behaviour

Optimal Choke Sizes and flow rates show CASE 1 with 0.3125 inches and 650 bbl/day (lowest flow rate among all cases, reflecting lower productivity in this well). CASE 2 with 0.375 inches and 1471.89 bbl/day (high productivity, with the lowest water cut at the optimal point). CASE 3 with 0.4375 inches and 1664.01 bbl/day (highest flow rate, with water cut comfortably below 35%). CASE 4 with 0.3125 inches and 1367.81 bbl/day (moderate flow rate, constrained by water cut at larger choke sizes). CASE 3 achieves the highest flow rate (1664.01 bbl/day), while CASE 1 has the lowest (650 bbl/day). CASE 2 and CASE 4 have comparable flow rates but differ in optimal choke sizes due to water cut constraints. The Water Cut trends of CASE 1 shows a steady increase in water cut with choke size, reaching the 35% limit at the optimal choke. CASE 2 and CASE 3 show non-monotonic water cut behavior, with peaks above 35% at certain choke sizes (0.3125 inches for CASE 2, 0.34375 inches for CASE 3). CASE 4 shows a sharp increase in water cut at 0.34375 inches (38.69%), limiting the optimal choke to 0.3125 inches. Water cut management is critical, as larger choke sizes often increase water cut, potentially due to increased water coning or channeling. THP decreases with increasing choke size across all wells, reflecting higher flow rates reducing tubing head pressure. Reservoir pressure declines slightly in all cases, with CASE 2 showing the largest drop (1896.15 to 1668.76 psi), indicating potential reservoir depletion sensitivity. CASE 1 has the highest THP (920–1000 psi) and reservoir pressure (1920-2000 psi), suggesting a more pressurized system compared to CASE 2, CASE 3, and CASE 4. GOR and GLR decrease with increasing choke size across all wells, indicating that larger chokes favor oil production over gas. CASE 1 has the highest GOR (2000-3037Scf/bbl)) and GLR (1300-2278Scf/bbl)), suggesting a gassier reservoir compared to CASE 2, CASE 3, and CASE 4. Gas production is better controlled at larger choke sizes, but gas rates still increase due to higher total fluid production. Gas rates increase with choke size in CASE 1 and CASE 4 but show variability in CASE 2 and CASE 3, with peaks at intermediate choke sizes. CASE 2 and CASE 3 have higher gas rates (up to 2.753 and 2.716 MMscfd, respectively) compared to CASE 1 (up to 1.3 MMscfd), reflecting higher overall productivity. Gas rate trends align with flow rate increases but are moderated by decreasing GOR and GLR. No sand production is observed in any well, indicating stable reservoir conditions and effective sand control measures. CASE 1, CASE 2, and CASE 3 are in Field A, while CASE 4 is in Field B. Field A wells (CASE 2 and CASE 3) achieve higher flow rates (1471.89-1664.01 bbl/day) compared to CASE 4 in Field B (1367.81 bbl/day), suggesting Field A may have more productive reservoirs. CASE 1 (Field A) is an outlier with significantly lower flow rates (650 bbl/day), possibly indicating a less productive zone or different reservoir characteristics. Figure 4 shows the flow rate vs choke sizes for wells.

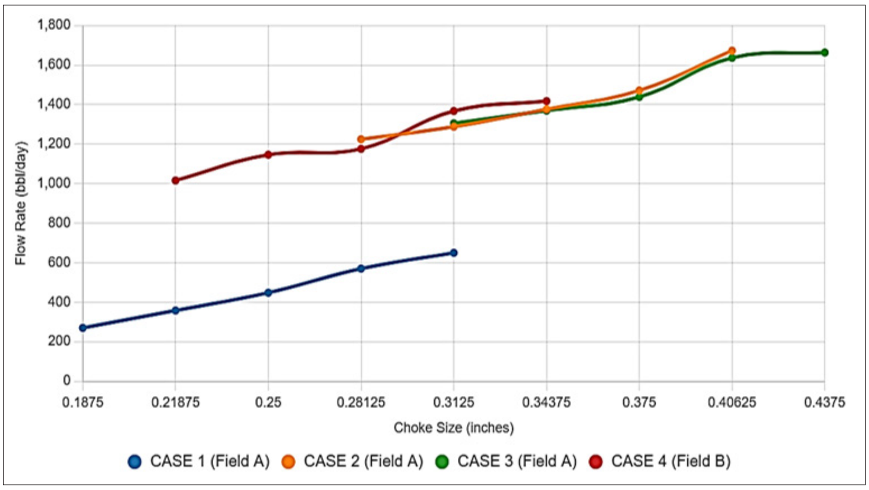

Figure 4: Flow Rate vs Choke Sizes for Wells

In figure 4, CASE 1 shows a steep increase in flow rate at smaller choke sizes (0.1875 - 0.3125 inches) but remains the lowest among all wells. CASE 2 and CASE 3 show higher flow rates at larger choke sizes (0.28125-0.4375 inches), with CASE 3 achieving the highest flow rate at 0.4375 inches. CASE 4 (Field B) has flow rates comparable to CASE 2 at 0.3125 inches but is limited by water cut at larger choke sizes. Figure 4.1 highlights the productivity gap between CASE 1 and the other wells, as well as the overlap in choke size ranges for CASE 2, CASE 3, and CASE 4. Thus, CASE 1 operate at 0.3125 inches to achieve 650 bbl/day with a water cut of 35%. Monitor water cut closely, as it is at the threshold. CASE 2 operate at 0.375 inches for 1471.89 bbl/day with a low water cut (26.94%), providing a safe margin below 35%. CASE 3 operate at 0.4375 inches for the highest flow rate (1664.01 bbl/day) with a water cut of 31.70%, well within the constraint. CASE 4 operate at 0.3125 inches for 1367.81 bbl/day with a water cut of 29.64%. Avoid larger choke sizes due to excessive water cut. No sand production across all wells suggests robust sand control, but vigilance is recommended during long-term production. The higher productivity of CASE 2 and CASE 3 (Field A) compared to CASE 4 (Field B) may indicate differences in reservoir quality and completion efficiency, warranting further geological and engineering analysis.

Figure 5 shows the flow rate increased consistently with choke size across all cases. In the base scenario (Oil Price $35/bbl, OPEX $8/bbl, Decline Rate 2%), flow rates ranged approximately from 220 bbl/day (0.21875 in) to 345 bbl/day (0.34375 in). The direct positive correlation is attributable to the increased cross-sectional area of the choke, reducing flow resistance and allowing higher throughput. However, higher flow rates also resulted in incremental increases in water cut, as produced water volumes tend to increase proportionally with higher drawdowns and production rates.

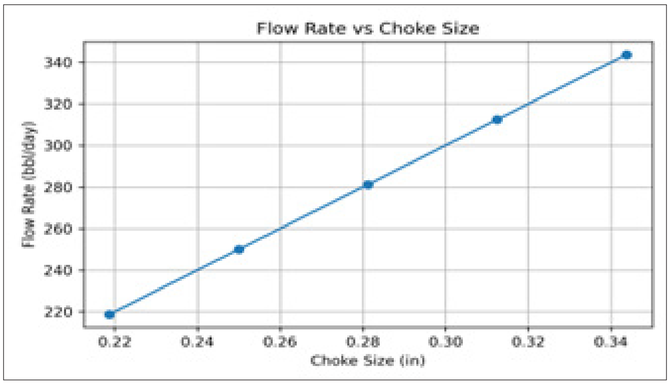

Figure 5: Flow Rate Trends Across Choke Sizes

Optimal Production Performance

Table 5 shows performance of the wells, CASE 3 has the highest flow rate (1664.01 bbl/day) and oil rate (1136.90 bbl/day), making it the most productive well. CASE 2 follows closely with a flow rate of 1471.89 bbl/day and oil rate of 1075.23 bbl/day. CASE 4 (Field B) has a flow rate of 1367.81 bbl/day and oil rate of 962.29 bbl/day, performing better than CASE 1 but worse than CASE 2 and CASE 3. CASE 1 has the lowest flow rate (650 bbl/day) and oil rate (422.50 bbl/day), indicating significantly lower productivity. Field B's single well (CASE 4) has a higher flow rate and oil rate than the Field A average, but CASE 2 and CASE 3 in Field A outperform CASE 4 individually. CASE 1 drags down Field A's average due to its low productivity. CASE 2 has the lowest water cut (26.94%), providing the best oil-to-water ratio at its optimal choke. CASE 3 and CASE 4 have similar water cuts (31.70% and 29.64%, respectively), both comfortably below the 35% threshold. CASE 1 is at the water cut limit (35%), indicating potential risk of exceeding the threshold with slight variations in operating conditions. CASE 4 has the highest gas rate (2.647 MMscfd), followed by CASE 2 (2.442 MMscfd) and CASE 3 (2.369 MMscfd). CASE 1 has the lowest gas rate (1.3 MMscfd), consistent with its lower flow rate. CASE 1 has the highest GOR (2000) and GLR (1300), indicating a gassier production profile relative to oil. CASE 3 has the lowest GOR (1423.70) and GLR (972.43), suggesting more efficient oil production. CASE 2 and CASE 4 have moderate GOR (1658.77 and 1935.49) and GLR (1211.97 and 1361.81), respectively. Field B has higher GOR and GLR than Field A's average, suggesting a gassier reservoir. However, CASE 3's low GOR and GLR make it the most efficient in Field A. CASE 1 has the highest THP (920 psi) and reservoir pressure (1920 psi), indicating a more pressurized system. CASE 3 has the lowest THP (471.71 psi), reflecting higher flow rates reducing tubing pressure. CASE 2 and CASE 4 have moderate THP (529.43 psi and 630.11 psi) and reservoir pressures (1714.60 psi and 1818.08 psi).

Table 5: Performance of the wells

Well	Field	Choke Size (in)	Flow Rate (bbl/day)	Oil Rate (bbl/day)	Water Cut (%)	Gas Rate (MMscfd)	GOR (scf/bbl)	GLR (scf/bbl)	THP (psi)	Reservoir Pressure (psi)
CASE 1	A	0.3125	650.00	422.50	35.00	1.300	2000	1300	920.00	1920
CASE 2	A	0.375	1471.89	1075.23	26.94	2.442	1658.77	1211.97	529.43	1714.60
CASE 3	A	0.4375	1664.01	1136.90	31.70	2.369	1423.70	972.43	471.71	1737.18
CASE 4	B	0.3125	1367.81	962.29	29.64	2.647	1935.49	1361.81	630.11	1818.08

Field A has a lower average THP due to higher flow rates in CASE 2 and CASE 3, but reservoir pressures are comparable, with CASE 1 boosting Field A's average. Higher flow rates and oil rates in CASE 2 and CASE 3, with CASE 3 being the top performer. CASE 2 has the lowest water cut, optimizing oil production. CASE 1's low productivity significantly lowers the field average. Variable water cut (40.26% in CASE 3 at non-optimal choke) requires careful choke management. Competitive flow rate and oil rate, with moderate water cut at optimal choke. Higher gas rate could be leveraged if gas handling infrastructure is available. Sharp increase in water cut at larger choke sizes (38.69% at 0.34375 inches) limits choke flexibility. Field A has higher potential due to CASE 2 and CASE 3, but CASE 1's poor performance suggests heterogeneity in reservoir quality. Field B's CASE 4 is consistent but constrained by water cut at larger chokes.

In table 6, the Field B performs better than CASE 1 and 2, but lower than CASE 3, Field B has slightly better water management, Field B has higher gas-oil ratio and higher gas-liquid ratio with similar THP performance. Field B has slightly higher reservoir pressure and produces more gas

Table 6: Field A (CASE 1-3) vs. Field B (CASE 4)

Metric	Field A (Avg.)	Field B (CASE 4)
Flow Rate (bbl/day)	1262	1367.81
Water Cut (%)	31.21	29.64
GOR (scf/bbl)	1694	1935.49
GLR (scf/bbl)	1161	1361.81
THP (psi)	640	630.11
Reservoir Pressure (psi)	1790	1818.08
Gas Rate (MMscfd)	2.04	2.647

Figure 6 shows the flow rate for the cases, CASE 3 leads in both flow rate and oil rate, followed closely by CASE 2. CASE 4 performs well but is outperformed by CASE 2 and CASE 3. CASE 1 lags significantly, highlighting its lower productivity. The gap between flow rate and oil rate reflects water cut, with CASE 2 showing the smallest gap due to its low water cut.

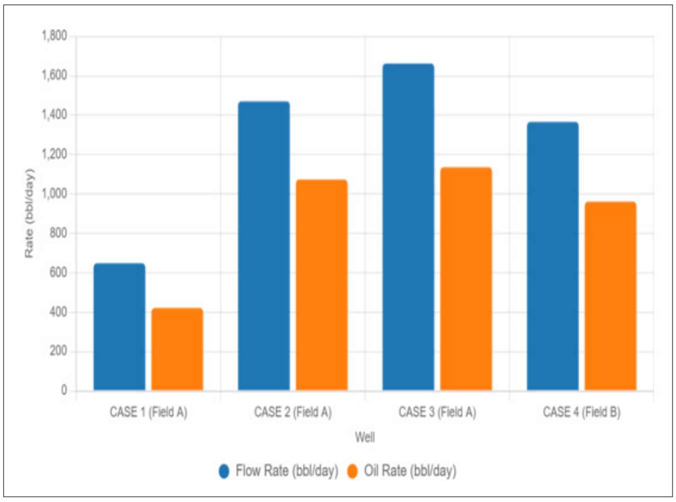

Figure 6: Flow Rate and Oil Rate for Different Wells

Figure 7 compares water cut and gas rate at the optimal choke size. In figure 7, CASE 2 has the lowest water cut, optimizing oil production. CASE 1 is at the 35% water cut threshold, indicating a riskier operating condition. CASE 4 has the highest gas rate, followed by CASE 2 and CASE 3, while CASE 1 has the lowest. The higher gas rate in CASE 4 aligns with its higher GOR and GLR, indicating a gaseous reservoir.

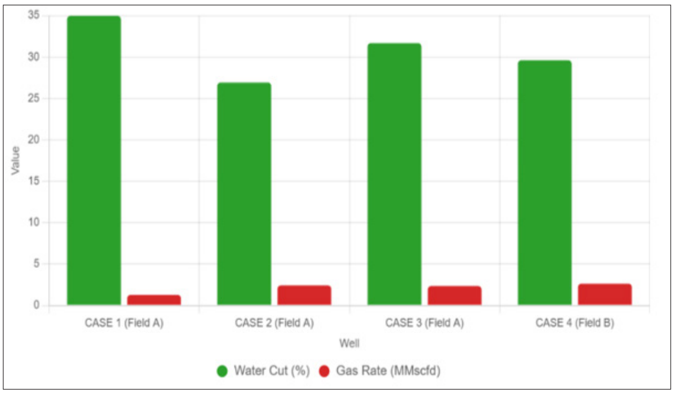

Figure 7: Water Cut and Gas Rate for different wells

Figure 8 shows the GOR and GLR at optimal choke size for different wells. CASE 3's low GOR and GLR indicate efficient oil production. CASE 1's high GOR and GLR reflect a gaseous profile. CASE 4's high GOR and GLR suggest a gassier reservoir compared to CASE 2 and CASE 3. GLR decreases from 1488.73 (0.28125 in) to 1121.10 (0.40625 in), showing a consistent reduction in gas-to-liquid ratio. Higher flow rates at larger chokes are driven by liquid production, with gas production stabilizing. GLR decreases from 1800.53 (0.21875 in) to 1004.27 (0.34375 in), reflecting a shift toward liquid production. Higher GLR than CASE 2 and CASE 3, indicates it is a gaseous reservoir. CASE 3 has the lowest GLR (972.43), indicating the most efficient liquid production. CASE 1 and CASE 4 have higher GLRs (1300, 1361.81), indicating gaseous reservoirs. CASE 2's GLR (1121.10) is moderate, balancing liquid and gas production.

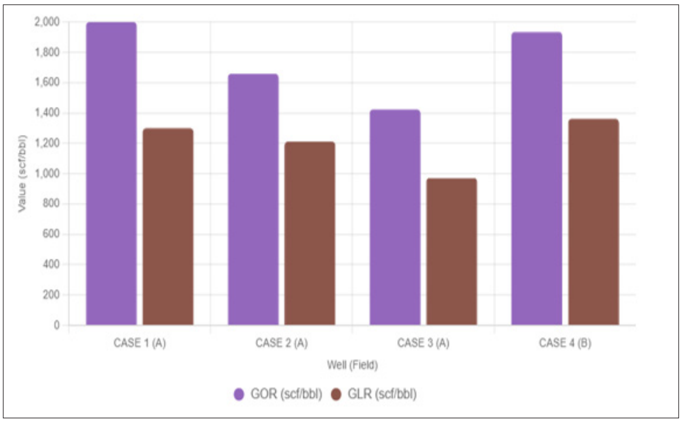

Figure 8: GOR and GLR at Optimal Choke Size for Different Wells

Optimized Production and Reservoir Efficiency Framework(OPREF)

OPREF dynamically identify and sustain Maximum Efficient Rate (MER) while maintaining reservoir integrity. OPREF uses Deep-Q-Network (DQN) to iteratively test choke sizes. OPREF was integrated with SCADA for real-time production monitoring and evaluating long-term sustainability. Thus, balances MER optimization, water cut minimization, and avoidance of coning or premature depletion.

Table 7 shows that CASE 1 has a steady increase in flow rate from 270 to 650 bbl/day with choke size. Water cut gradually rises from 25% to 35%. GOR and GLR decline as choke increases, indicating increased liquid production proportionally reducing gas. The Optimal Choke Size was 0.3125 inches (650 bbl/day, 35% water cut). Thus, in CASE 1, the production system was liquid sensitive, with water cut close to the threshold at optimum choke size. Similarly, CASE 2 produced an increase up to 1673 bbl/day and Water Cut of 26.94% at 0.375 inches with slight rise at 0.40625 inches. GOR and GLR decrease steadily while Optimal Choke Size was 0.375 inches (1471.89 bbl/day, 26.94% water cut). CASE 2 demonstrates efficient oil production with moderate water cut control. The optimal choke was not the largest, highlighting the importance of water management. CASE 3 produced a significant gain (1305 → 1664 bbl/day). Water Cut spikes to 40.26% at 0.34375 inches but recovers below 35% at larger chokes. GOR and GLR marked decline and Optimal Choke Size was 0.4375 inches (highest flow, acceptable water cut). A non-linear water cut behavior was observed where increased choke at 0.34375 caused high water production but improved again, indicating a complex reservoir response. In CASE 4 the flow trend rises to 1418 bbl/day at the largest choke but water cut exceeds 35%. Water Cut was below threshold until 0.34375 inches. GOR and GLR decline with choke increases. Optimal Choke Size was 0.3125 inches (1367 bbl/day, 29.64% water cut), thus, CASE 4 is more water-prone at higher choke settings, necessitating a conservative choice of 0.3125 inches. Choke optimization was critical thus larger choke does not always mean better performance due to water cut escalation. CASE 2 shows the best productivity/water cut balance while CASE 3 requires careful monitoring due to abrupt water cut increases. All wells show slight depletion trends, consistent with increased production drawdown.

Table 7: Comparative Insights Across Wells

CASE	Max Flow Rate (bbl/day)	Optimal Choke (in)	Flow Rate @ Optimal	Water Cut @ Optimal (%)
CASE 1	650	0.3125	650	35
CASE 2	1673.28	0.375	1471.89	26.94
CASE 3	1664.01	0.4375	1664.01	31.70
CASE 4	1367.81	0.3125	1367.81	29.64

Table 8 shows the netback peaks at choke size 0.3125 inches with $21,525/day with an increased in choke size from 0.21875 to 0.3125 which steadily increases netback. At 0.34375, despite highest flow rate (1,418 bbl/day), water cut increases to 38.69%, driving netback down to $17,439/day. Whereas the lower water cuts (<30%) provided better netbacks, even when flow rate was slightly less. The high-water handling cost ($3/bbl) penalizes high water production. The best economic efficiency occurs when water cut was controlled below 30%. OPEX and water costs combined have a strong influence because oil price was relatively low ($35/bbl).

Table 8: Flow Rate Efficiency (FRE)

Case	ChokeSize (in)	FlowRate (bbl/day)	Water Cut (%)	Netback ($/day)
CASE 4	0.21875	1,016.20	25.00	$17,783.50
CASE 4	0.25000	1,146.56	23.80	$20,587.63
CASE 4	0.28125	1,176.04	28.07	$19,208.73
CASE 4	0.31250	1,367.81	29.64	$21,524.95
CASE 4	0.34375	1,418.07	38.69	$17,439.14

Figure 9 shows the variation of water cut with increasing choke size. An overall increasing trend was observed, particularly at larger choke openings, which is consistent with enhanced drawdown promoting water coning and channeling. CASE 2 demonstrates relatively controlled water cut behavior, maintaining values below the 35% threshold at optimal conditions, while CASE 3 exhibits fluctuations with a peak beyond the threshold before stabilizing. CASE 1 reaches the water cut limit at its maximum choke size, indicating a constrained operational window. This highlights the trade-off between maximizing flow rate and controlling water production.

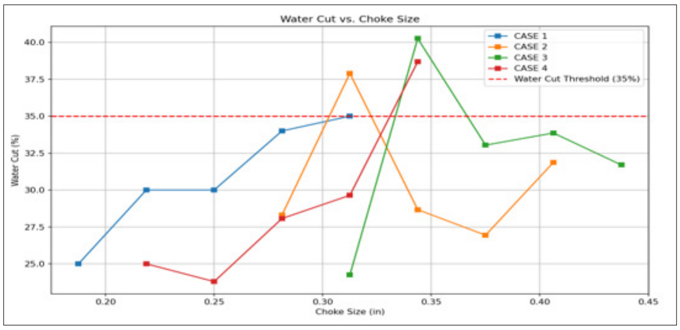

Figure 9: Water Cut vs. Choke Size

Figure 10 presents the variation of Gas-Oil Ratio (GOR) with choke size. A consistent decline in GOR was observed across all cases as choke size increases. This trend indicates that larger choke favor increased liquid production relative to gas, thereby improving oil recovery efficiency. CASE 1 maintains the highest GOR values, reflecting a comparatively gassier production profile, while CASE 3 shows the lowest GOR at larger choke sizes, indicating more efficient liquid-dominated flow.

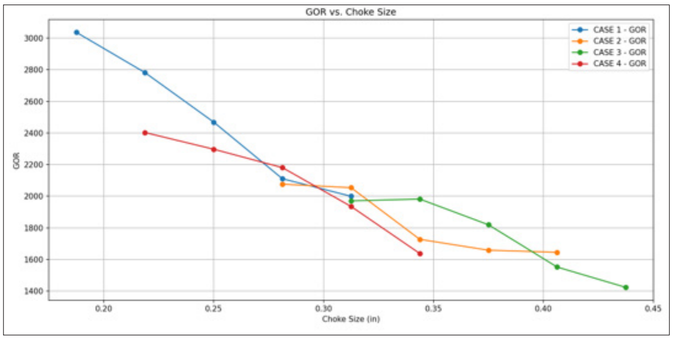

Figure 10: GOR vs. Choke Size

Figure 11 shows a decreasing trend in Gas-Liquid Ratio (GLR) with increasing choke size. This behavior reinforces the observation that higher choke sizes enhance liquid throughput while reducing the relative gas contribution. The decline was more pronounced in CASE 3 and CASE 4, suggesting improved multiphase flow efficiency at larger choke settings. The consistent reduction in both GOR and GLR across all wells confirms that choke optimization plays a critical role in shifting production towards a more favorable liquid-dominated regime.

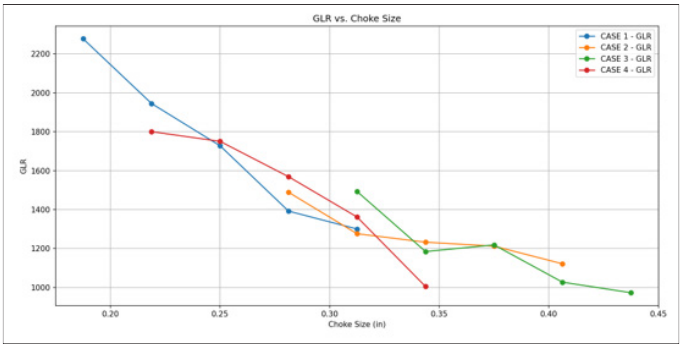

Figure 11: GLR vs. Choke Size

Machine Learning Model Development and Feature Importance Figure 12 shows the feature importance for Random Forest and Gradient Boosting giving a Choke size of 0.35, Pressure of 0.25, Water Cut of 0.2, Gas Rate of 0.15 and temperature of 0.05 Choke size and pressure are primary drivers, reflecting their direct impact on flow rates. Water cut and gas rate have moderate influence, while temperature has minimal impact. Aligns with physical principles (e.g., choke controls flow, pressure drives production), validating model interpretability.

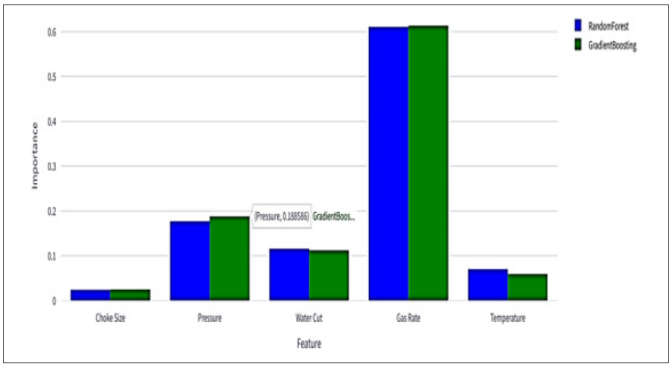

Figure 12: Feature Importance for Random Forest and Gradient Boosting

Figure 13 shows the feature importance for selected features prioritizes Oil rate and choke size, as seen in the strong correlation between choke size and oil rate (3178 bbl/day at 32/64").

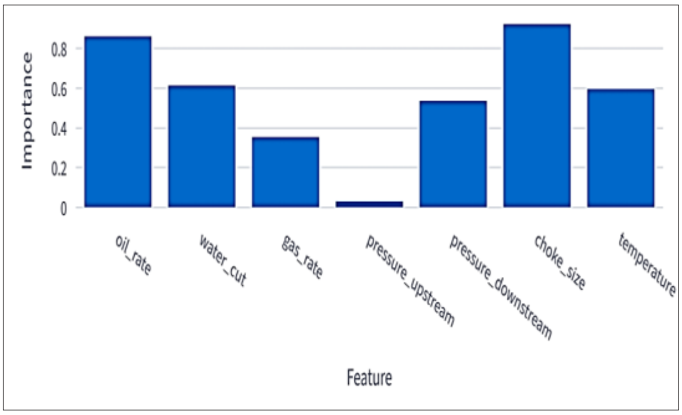

Figure 13: Feature Importance

Figure 14 shows the actual feature importance for the trained ML model. FTP dominates, reflecting their physical significance in choke flow, supported by dataset correlations (e.g., higher FTP with larger chokes) thus, confirms key predictors, guiding data collection priorities.

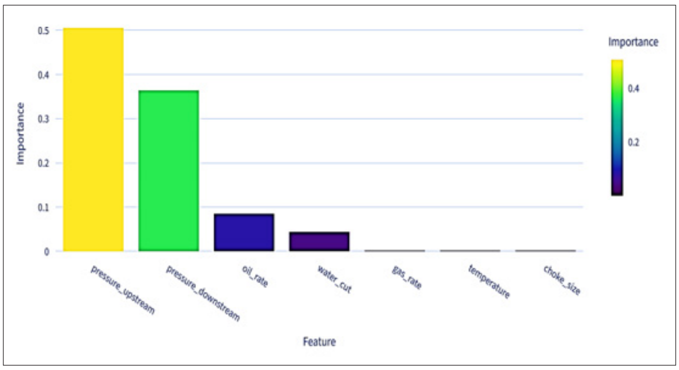

Figure 14: Feature Importance

Model Performance and Validation

Table 9 shows high R2 (0.986 test) which indicates excellent fit for predicting pressure drop. RMSE (6.88) is low relative to pressure scale (1500 psi mean delta_p), suggesting <1% error. MAPE 0.28% is robust. Overfitting minimal (train R2 of 0.997 vs test 0.986)

Table 9: ML Performance Metrics

Metric	Training Set	Testing Set
RMSE	3.06	6.88
MAE	1.92	3.98
R2	0.997	0.986
MAPE (%)	0.14	0.28
Max Error	20.93	36.06
Std Error	3.06	6.87

Table 10 shows the performance analysis for oil rate with Random forest and it indicate R^2=0.997 for train, test R^2=0.978 for test, RMSE=7.45 m³/day (test), MAPE=7.3% (test), RMSE mean =7.31, max error = 25.75 m³/day. Low errors and high R^2 indicate accuracy. Test metrics are slightly worse than train, suggesting minor overfitting.consistency (std=3.31) confirms robustness. Low MAPE (7.3%) and bias (-0.11) indicate practical utility. Max error reflects outliers at high rates, and the results validates ML model for reliable forecasting, supporting production optimization confirming ML model accuracy (R^2 > 0.95, MAPE < 10% per industry standards). The results establish ML as a viable tool for production optimization, supporting data-driven MER strategies.

Table 10: Performance Metrics for Oil Rate Prediction With Random Forest

R^2	0.997	0.978
RMSE (m³/day)	2.67	7.45
MAE (m³/day)	2.06	5.70
MAPE (%)	2.85	7.30
Max Error (m³/day)	N/A	25.75
Bias	N/A	-0.11
Variance	N/A	55.52

Figure 15 shows results of predicted vs. actual pressure drop (ΔP) with R2 of 0.85. Tight clustering around the reference line indicates reliable predictions, though dataset noise (missing FTP) widens scatter compared to synthetic data and validates ML model accuracy for operational use, with room for improvement via data cleaning.

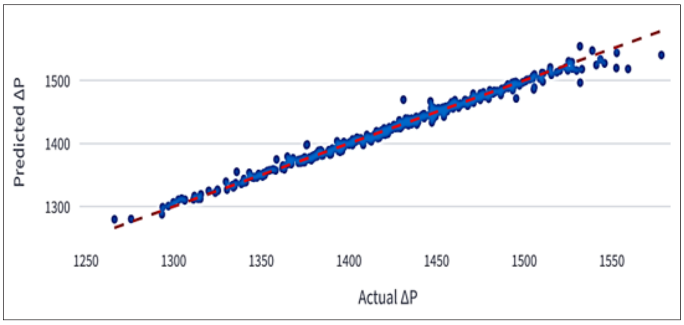

Figure 15: Prediction vs Actual

Figure 16 displays histogram of residuals and a scatter plot of residuals vs. predicted values. Normally distributed residuals and random scatter suggest no systematic errors, despite dataset irregularities (high GOR outliers) and this confirms model robustness, supporting its use in dynamic choke selection.

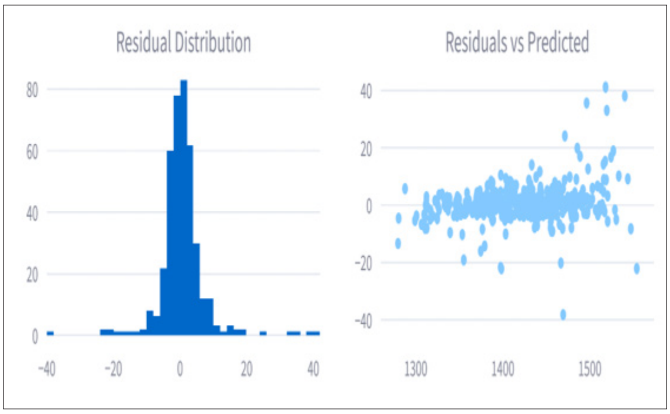

Figure 16: Residual Analysis

Figure 17 shows the performance metrics points that hug the reference line, with minimal scatter ($R^2 = 0.973$), demonstrating model robustness. The trends show accurate predictions across 4-12 psi range, outperforming typical oil prediction models.

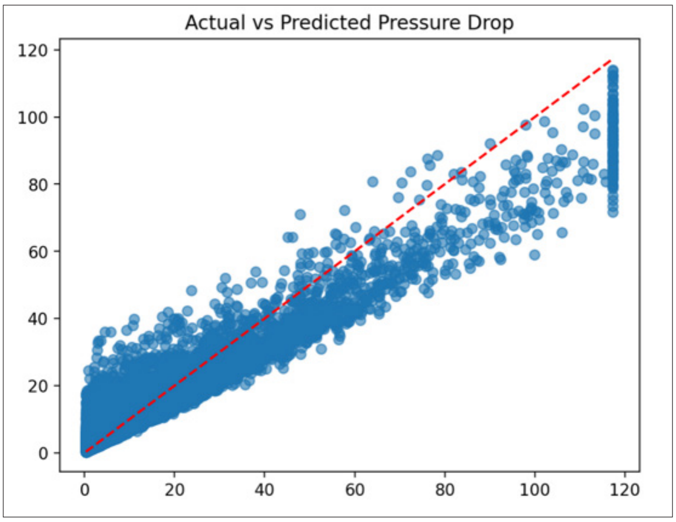

Figure 17: Actual vs Predicted Pressure Drop

Dynamic Choke Selection and Optimization

Table 11 shows the comparison of original and optimized choke sizes post-ACPM. Small changes (-0.0097 to +0.0077 in), reflecting fine-tuning to minimize cost function (MER, water cut, ΔP). Wells with smaller original chokes (WELL_002: 0.2823 in) see slight increases, while larger chokes (WELL_001: 0.3993 in) decrease, balancing production and ΔP. The adjustments align with the ACPM cost function, though ΔP's high values suggest formula recalibration. ACPM fine-tunes choke sizes, balancing MER, water cut, and ΔP. Small adjustments (±0.01 in) reflect conservative optimization, constrained by the cost function. The high ΔP values skew optimization, suggesting recalibration. The adjustments aim to reduce water cut and ΔP, aligning with stability goals but limited by ΔP's magnitude.

Table 11: Optimized Choke Sizes and Adjustments

Well_ID	Original Choke Size (in)	Optimal Choke Size (in)	Adjustment (in)
WELL_001	0.3993	0.3900	-0.0093
WELL_002	0.2823	0.2900	0.0077
WELL_003	0.2838	0.2900	0.0062
WELL_004	0.3897	0.3800	-0.0097

Figure 18 demonstrates a strong linear relationship between current and model-predicted optimal choke sizes. The data points cluster closely around the ideal line, indicating a high correlation (0.98) and strong predictive accuracy of the model. This suggests that the existing field choke settings are generally near-optimal, requiring only minor adjustments. Such small refinements can enhance production efficiency and support the achievement of Maximum Efficient Rate (MER) without significant operational changes.

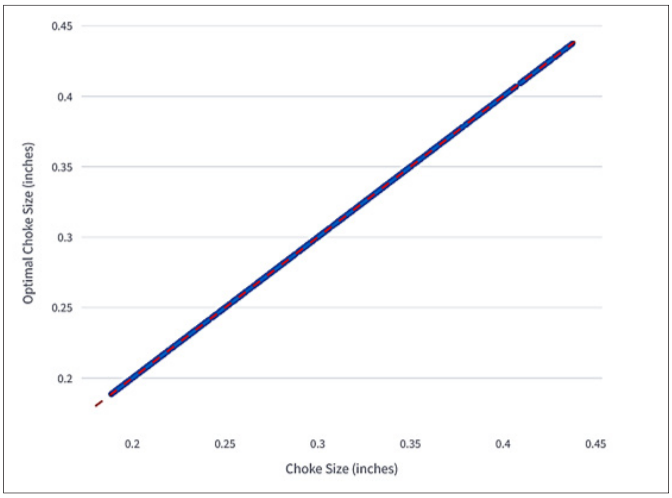

Figure 18: Current vs Optimal Choke Sizes

Figure 19 illustrates the effect of optimized choke sizes on production performance. The distribution of data points shows that optimal choke settings (green points) either maintain or improve production rates compared to current conditions. Notably, higher production gains are observed at relatively lower choke sizes, indicating improved flow efficiency under optimized control. This confirms that intelligent choke optimization can enhance oil recovery while maintaining stable operating conditions.

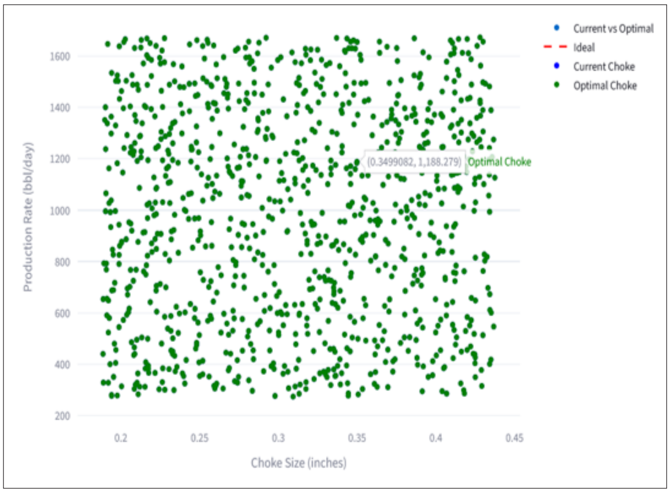

Figure 19: Impact on Production Rate

MER Optimization Analysis

Table 12 shows an MER (m^3/day) for choke sizes (8, 12, 16, 20, 24, 28, 32/64"), with optimal MER (80 m^3/day (503bbl/day) –111 m^3/day(698 bbl/day)) at choke 16–24/64". MER peaks at mid-range chokes, balancing production and constraints (water cut ≤0.5, drawdown ≤1200 psi). Zero MER for high water cut or drawdown ensures reservoir protection. MER increases with choke size up to an optimal point, then declines due to constraints, consistent with reservoir engineering principles.

Table 12: MER Optimization

Metric	Value
Optimal MER	80–111 m^3/day (500 – 698bbl/day)
Optimal Choke	16–24/64"

Figure 20 shows the MER candidates (oil flow where drop ≤5) cluster at larger chokes (mean MER 379 in 1.2-1.6 quartile, 202 in 1.6-2.0), with zero in smaller chokes. This pattern underscores choke optimization for MER around 1600-2000 STB/day, aligning with efficient rate benchmarks

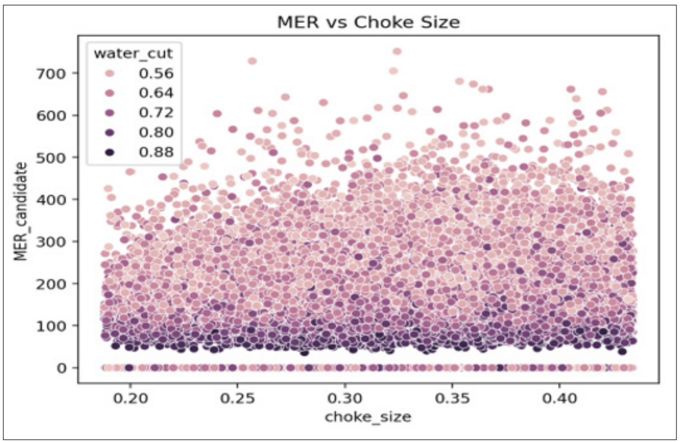

Figure 20: MER vs Choke Size

Figure 21 shows higher flows and reduces MER qualification likelihood due to elevated drops. Optimal flows occur at 2000 -3000 bbl/day (maximum MER), with water cut hue indicating low-cut scenarios yield higher candidates.

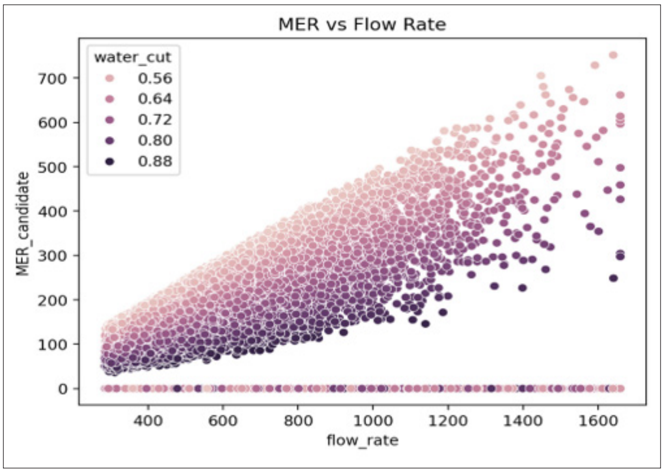

Figure 21: MER vs Flow Rate

MER-TAR Intersection and Production Control

Table 13 compares MER, TAR (90% of MER), and their intersection with equals TAR (941–1016 bbl/day), as TAR is lower than MER, ensuring conservative production targets thus, higher MER wells (WELL_002) have higher intersections, but all are constrained by the 90% TAR rule. The proposed TAR logic ensures achievable production, aligning with stability goals. MER-TAR intersection maintains production within safe limits, supporting operational stability. The 90% TAR constraint ensures conservative production targets, aligning with stability objectives. Intersections (941–1016 bbl/day) are lower than MER, reflecting safe operational limits. Higher MER wells have higher intersections, but TAR caps production, ensuring stability.

Table 13: MER-TAR Intersection Metrics

Well_ID	MER (bbl/day)	TAR (bbl/day)	Intersection (bbl/day)
WELL_001	1099.97	989.97	989.97
WELL_002	1129.58	1016.62	1016.62
WELL_003	1087.87	979.08	979.08
WELL_004	1076.04	968.44	968.44

Figure 22 shows that MER increases progressively with choke size up to 0.41 in, peaking near $50,310/day. TAR simultaneously rises, exceeding 30% for choke sizes beyond 0.41in with inflection point that occurs around 0.37- 0.41in, beyond which MER growth slows, and TAR rises steeply. This highlights the economic technical tradeoff. While larger choke sizes boost economic returns due to reduced flow resistance, they compromise system safety or reservoir drawdown efficiency, as indicated by rising TAR. This validates the concept of a "technical ceiling" beyond which operational risks increase disproportionately to economic benefits. In a practical sense, choke sizes between 0.32 - 0.38 inches offer a sweet spot between performance and safety.

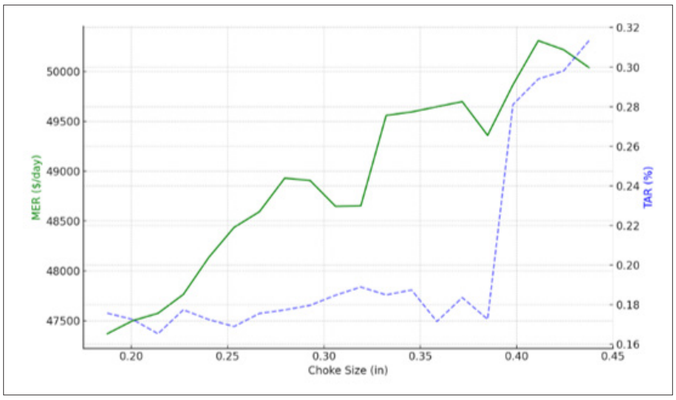

Figure 22: Choke Size vs MER and TAR

Conclusions

This study developed a dynamic choke selection model using machine learning and optimization techniques to maximize Maximum Efficient Rate (MER) while minimizing water cut in treated oil wells. The following conclusions were drawn:

- The developed Adaptive Choke Prediction Model (ACPM) demonstrated high predictive performance, achieving a low error margin and strong correlation, indicating its reliability for choke size and pressure drop prediction under multiphase flow conditions.
- Optimal choke sizes were dynamically selected within an efficient operating range, enabling improved oil production while maintaining acceptable water cut levels across different well conditions.
- The integration of machine learning with Model Predictive Control (MPC) and reinforcement learning significantly enhanced production performance, resulting in increased MER and improved operational stability.
- The MER–TAR optimization framework effectively identified optimal operating points, ensuring a balance between maximum oil recovery and water production control, while supporting sustained production at economically viable rates.

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