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Data-Driven Oil Production Decline Prediction by K-Nearest Neighbors Algorithm A Big Data Analytics Approach

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Abstract

The petroleum industry faces significant challenges in optimizing production and predicting decline patterns in mature oil fields. Traditional decline curve analysis methods often lack the precision required for modern reservoir management. This study presents a novel application of the k-Nearest Neighbors (k-NN) machine learning algorithm for predicting oil production decline and determining optimal intervention strategies in Well No. 807, a 2,400-meter deep well located in a northern Russian oil field. Using production data spanning from 2013 to 2024, we developed and validated a k-NN model that incorporates multiple distance metrics including Euclidean, Manhattan, and Minkowski distances. The model achieved 87.3% prediction accuracy with an R^2 value of 0.89, demonstrating superior performance compared to traditional forecasting methods. Our analysis identified critical intervention points at months 18, 36, and 54 of the production cycle, with potential production improvements of 15-25% following well stimulation activities. The weighted k-NN approach with k=7 and Euclidean distance metric provided the most reliable predictions. Feature importance analysis revealed that reservoir pressure (35%) and water cut (28%) were the most significant predictors of production decline. This research contributes to the growing body of knowledge in petroleum data analytics and provides practical insights for production optimization in mature oil fields. The methodology can be extended to other wells and reservoirs, offering significant economic benefits through improved production forecasting and timely intervention strategies.

Keywords: oil production prediction, k-nearest neighbors, machine learning, petroleum engineering, production optimization, data mining, predictive analytics

التنبؤ بانخفاض إنتاج النفط استنادًا إلى البيانات باستخدام خوارزمية أقرب الجيران (K-Nearest Neighbors) - نهج تحليل البيانات الضخمة

لؤي فؤاد علي عبد المجيد

الملخص

يواجه قطاع البترول تحديات كبيرة في تحسين الإنتاج والتنبؤ بأنماط الانخفاض في الحقول النفطية الناضجة. وغالبًا ما تفتقر طرق تحليل منحنيات الانخفاض التقليدية إلى الدقة المطلوبة لإدارة الخزانات الحديثة. تقدّم هذه الدراسة تطبيقًا جديدًا لخوارزمية التعلّم الآلي القائمة على أقرب الجيران **(k-NN)** للتنبؤ بانخفاض إنتاج النفط وتحديد استراتيجيات التدخل المثلى في البئر رقم 807، وهو بئر بعمق 2400 متر يقع في حقل نفطي شمالي في روسيا. باستخدام بيانات الإنتاج الممتدة من عام 2013 إلى عام 2024، قمنا

بتطوير وتصديق نموذج **k-NN** يدمج مقاييس مسافة متعددة، بما في ذلك المسافات الإقليدية، ومنهاتن، ومينكوفسكي. حقق النموذج دقة تنبؤ بلغت 87.3% مع قيمة **R^2** تساوي 0.89، مما يدل على أداء أفضل مقارنةً بالطرق التنبؤية التقليدية. وقد حدد تحليلنا نقاط تدخل حرجة عند الشهور 18 و36 و54 من دورة الإنتاج، مع إمكانية تحسين الإنتاج بنسبة تتراوح بين 15% و25% بعد إجراء عمليات تحفيز البئر. وقد قدّم نهج **k-NN** المرجّح مع **k=7** واستخدام مقياس المسافة الإقليدية أكثر التنبؤات موثوقيةً. وكشف تحليل أهمية المتغيرات أن ضغط الخزان (35%) ونسبة المياه (28%) كانا أكثر العوامل تأثيرًا في تنبؤ انخفاض الإنتاج. تسهم هذه الدراسة في توسيع قاعدة المعرفة في مجال تحليل البيانات البترولية، وتوفر رؤى عملية لتحسين الإنتاج في الحقول النفطية الناضجة. ويمكن تعميم المنهجية المُعتمدة على آبار وخزانات أخرى، مما يحقق فوائد اقتصادية كبيرة من خلال تحسين دقة التنبؤ بالإنتاج وتوقيت استراتيجيات التدخل بشكل أمثل.

الكلمات المفتاحية: التنبؤ بإنتاج النفط، أقرب الجيران**(k-NN)** ، التعلّم الآلي، هندسة البترول، تحسين الإنتاج، تنقيب البيانات، التحليلات التنبؤية

I. INTRODUCTION

A. Significance of the Study

The global petroleum industry generates over $3 trillion annually, with production optimization being crucial for maintaining economic viability and meeting energy demands [1]. As conventional oil reserves mature, operators face increasing challenges in maintaining production rates while managing operational costs. The decline in oil production from mature fields represents one of the most significant technical and economic challenges in petroleum engineering, with global production declining at an average rate of 6-8% annually in mature reservoirs [2].

Traditional production forecasting methods, such as Arps decline curve analysis, often fail to capture the complex non-linear relationships between reservoir parameters and production performance [3]. These limitations become particularly pronounced in mature fields where production behavior is influenced by multiple factors including reservoir heterogeneity, fluid properties, and operational constraints. The need for more sophisticated predictive models has led to increased interest in machine learning applications within the petroleum industry [4].

Predictive analytics using machine learning algorithms offers unprecedented opportunities to improve decision-making processes in oil field operations. By leveraging historical production data and advanced algorithms, operators can anticipate production trends, optimize intervention strategies, and maximize ultimate recovery [5]. The economic impact of improved prediction accuracy is substantial, with studies indicating that 10% improvement in production forecasting can result in 2-5% increase in field net present value [6].

B. Research Objectives

This research aims to address the limitations of conventional production forecasting through the following specific objectives:

1. **Develop a robust k-NN model** for oil production forecasting that can accurately predict decline patterns in Well No. 807, incorporating multiple reservoir and operational parameters.
2. **Identify optimal intervention timing** by analyzing production trends and determining critical decision points where well interventions can maximize production recovery.
3. **Compare distance metrics performance** by evaluating Euclidean, Manhattan, and Minkowski distances to determine the most effective similarity measure for oil production data.
4. **Provide actionable recommendations** for field operators regarding well stimulation, maintenance scheduling, and production optimization strategies based on predictive model outputs.

C. Research Questions

This study addresses the following research questions:

1. **Prediction Accuracy:** How accurately can the k-NN algorithm predict oil production decline in mature wells compared to traditional forecasting methods?
2. **Model Optimization:** What is the optimal k value for the k-NN algorithm when applied to oil production time series data from Well No. 807?
3. **Distance Metrics:** Which distance metric (Euclidean, Manhattan, or Minkowski) provides the best performance for similarity measurement in oil production prediction?
4. **Intervention Timing:** When should production enhancement interventions be implemented to maximize recovery and economic returns?

D. Research Hypotheses

Based on literature review and preliminary analysis, the following hypotheses are proposed:

1. **H_1:** The k-NN algorithm can predict oil production decline with greater than 85% accuracy, outperforming traditional decline curve analysis methods.
2. **H_2:** Weighted k-NN algorithm will demonstrate superior performance compared to standard k-NN by accounting for distance-based similarity in production patterns.
3. **H_3:** Euclidean distance metric will provide the best results for oil production prediction due to its ability to capture multidimensional relationships between reservoir parameters.

4. **H_4:** Early intervention indicators can be identified through k-NN analysis, enabling proactive well management strategies that improve ultimate recovery by 15-25%.

II. LITERATURE REVIEW

2.1 Historical Overview of Production Forecasting Methods

Production forecasting in petroleum engineering has evolved significantly over the past century. Early methods relied primarily on empirical decline curves proposed by Arps in 1945, which assumed exponential, hyperbolic, or harmonic decline patterns [1]. While these methods provided reasonable approximations for conventional reservoirs, they often failed to capture the complex behavior of heterogeneous formations and unconventional resources [2].

Fetkovich expanded upon Arps' work by incorporating type curves that combined transient flow analysis with boundary-dominated flow, providing better
representation of reservoir physics [3]. However, these analytical methods still struggled with the non-linear nature of production decline in complex reservoir systems. The introduction of reservoir simulation in the 1960s offered more sophisticated modeling capabilities but required extensive data and computational resources [4].

Recent developments have focused on hybrid approaches combining physics-based models with statistical methods. Bayesian approaches have gained popularity for incorporating uncertainty quantification in production forecasts [5]. Despite these advances, traditional methods continue to face limitations in handling large datasets and capturing complex multivariable relationships.

2.2 Machine Learning in Petroleum Engineering

The application of machine learning in petroleum engineering has expanded rapidly since the 2000s, driven by advances in computational power and data availability [6]. Early applications focused on well log interpretation and reservoir characterization using neural networks and support vector machines [7]. Mohaghegh demonstrated the potential of artificial intelligence in petroleum engineering through various case studies, establishing the foundation for modern applications [8].

Production optimization has emerged as a key application area for machine learning algorithms. Artificial neural networks have been successfully applied to production forecasting in various field studies, showing improved accuracy compared to traditional methods [9]. Random forest and ensemble methods have demonstrated effectiveness in handling high-dimensional datasets common in petroleum applications [10].

Recent studies have explored deep learning applications for production prediction, with convolutional neural networks showing promise for analyzing spatial data from reservoir models. However, these methods often require extensive training data and may suffer from overfitting in datasets with limited observations [11].

2.3 k-NN Algorithm Applications in Time Series

The k-Nearest Neighbors algorithm has found numerous applications in time series forecasting across various industries. Martinez and Martinez provided comprehensive coverage of k-NN applications in pattern recognition and data mining [12]. The algorithm's non-parametric nature makes it particularly suitable for datasets where underlying relationships are complex or unknown [13].

In financial time series, k-NN has been successfully applied to stock price prediction and market volatility forecasting. The algorithm's ability to adapt to changing
patterns without requiring model retraining makes it attractive for dynamic systems [14]. Energy demand forecasting has also benefited from k-NN applications, with studies showing competitive performance compared to traditional econometric models [15].

The key advantage of k-NN in time series applications is its ability to capture local patterns and adapt to non-stationary behavior. However, the algorithm's performance is heavily dependent on feature selection, distance metric choice, and k value optimization [16].

2.4 Distance Metrics Comparison Studies

Distance metric selection significantly impacts k-NN algorithm performance. Comprehensive studies by Chomboon et al. evaluated multiple distance metrics across various datasets, finding that Euclidean and Manhattan distances generally provide robust performance [17]. However, the optimal choice depends on data characteristics and problem domain.

In petroleum applications, Euclidean distance has been commonly used due to its ability to capture multidimensional relationships between reservoir parameters. Studies in production forecasting have shown that weighted distance measures can improve prediction accuracy by emphasizing more relevant features [18]. The choice of distance metric becomes particularly important when dealing with heterogeneous datasets containing variables with different scales and units.

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2.5 Production Optimization Strategies

Modern production optimization strategies integrate predictive analytics with operational decision-making. Real-time optimization systems have been developed to continuously adjust production parameters based on current conditions and forecasted trends [19]. These systems typically combine reservoir models with economic optimization to maximize net present value [20].

Well intervention strategies have evolved from reactive maintenance to predictive interventions based on performance indicators. Machine learning models can identify patterns that precede production decline, enabling proactive interventions that maintain production rates [21]. The integration of IoT sensors and real-time data analytics has further enhanced the capability for predictive interventions.

2.6 Gap Analysis and Research Contribution

Despite significant advances in machine learning applications for petroleum engineering, several gaps remain in the literature. Limited studies have specifically
evaluated k-NN algorithm performance for oil production prediction in mature fields [22]. Most existing research focuses on unconventional resources or short-term production forecasting, leaving a gap in long-term prediction for conventional reservoirs.

Furthermore, few studies have comprehensively compared distance metrics for petroleum data or provided practical guidance for intervention timing based on predictive model outputs. This research addresses these gaps by providing a detailed evaluation of k-NN algorithm performance, distance metric comparison, and practical intervention recommendations for mature oil field operations [23].

III. METHODOLOGY

3.1 Data Collection

The study utilizes production data from Well No. 807, located in a northern Russian oil field. The well specifications are as follows:

- **Well Depth:** 2,400 meters (7,874 feet)
- **Location:** Northern Russian oil field
- **Production Period:** January 2013 to December 2024
- **Reservoir Type:** Conventional sandstone reservoir

- **Initial Production Rate:** 450 barrels per day (bbl/day)
- **Current Production Rate:** 180 bbl/day

The dataset comprises 144 monthly observations with the following variables: production rate (bbl/day), wellhead pressure (psi), reservoir temperature (°F), water cut (%), gas-oil ratio (scf/bbl), and operational status indicators. Data quality assessment revealed 3.2% missing values, primarily in gas-oil ratio measurements during maintenance periods.

3.2 Data Preprocessing

3.2.1 Missing Value Handling

Missing values were addressed using linear interpolation for time series continuity. For gas-oil ratio measurements, missing values were imputed using k-NN imputation with k=3, considering the temporal nature of the data and correlation with production rate.

3.2.2 Normalization Techniques

Min-max normalization was applied to ensure all features contribute equally to distance calculations:

$$X_{normalized} = (X - X_{min}) / (X_{max} - X_{min})$$

3.2.3 Feature Engineering

Additional features were created to enhance model performance:

- Production rate change (month-over-month)
- Cumulative production
- Pressure decline rate
- Water cut acceleration
- Seasonal indicators

3.3 k-NN Algorithm

3.3.1 Mathematical Foundation

The k-Nearest Neighbors algorithm predicts production values based on the k most similar historical observations. For a given query point x, the prediction is calculated as:

$$\hat{y} = (1/k) \Sigma_{i=1}^{k} y_i$$

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where y_i represents the production values of the k nearest neighbors.

3.3.2 Distance Metrics

Three distance metrics were evaluated for similarity measurement:

Euclidean Distance:

$$dE(x,y) = \sqrt{(\Sigma_{i=1}^{n}(x_i - y_i)^2)}$$

Manhattan Distance:

$$d_M(x,y) = \Sigma_{i=1}^{n}|x_i - y_i|$$

Minkowski Distance:

$$d_{Mi}(x,y) = (\Sigma_{i=1}^{n}|x_i - y_i|^p)^{1/p}$$

where p=3 was used for Minkowski distance calculations.

3.3.3 Weighted k-NN

To account for varying similarity levels, weighted k-NN was implemented:

$$\hat{y} = \Sigma_{i=1}^{k} w_i y_i / \Sigma_{i=1}^{k} w_i$$

where weights are calculated as:

$$w_i = 1 / (d_i^2 + \varepsilon)$$

with ε = 1e-6 to prevent division by zero.

3.3.4 k Value Optimization

Grid search with 5-fold cross-validation was employed to determine optimal k values, testing k ∈ {3, 5, 7, 9, 11, 13, 15}. The optimal k value was selected based on minimum cross-validation error.

3.4 Feature Selection

Feature importance was evaluated using correlation analysis and mutual information. The final feature set included:

1. Production rate (lagged 1-3 months)
2. Wellhead pressure
3. Reservoir temperature
4. Water cut percentage
5. Gas-oil ratio
6. Cumulative production
7. Production rate change

3.5 Model Evaluation Metrics

Model performance was assessed using multiple metrics:

Mean Absolute Error:

$$MAE = (1/n)\ \Sigma_{i=1}^{n}\ |y_i - \hat{y}_i|$$

Root Mean Square Error:

$$RMSE = \sqrt{(1/n)\ \Sigma_{i=1}^{n}\ (y_i - \hat{y}_i)^2}$$

R-squared:

$$R^2 = 1 - (SS_{res} / SS_{tot})$$

Mean Absolute Percentage Error:

$$MAPE = (100/n)\ \Sigma_{i=1}^{n}\ |((y_i - \hat{y}_i) / y_i)|$$

3.6 Implementation Environment

The k-NN algorithm was implemented in C# using .NET 6.0 framework with the following libraries:

- ML.NET for machine learning operations
- Math.NET Numerics for statistical calculations
- ScottPlot for data visualization
- CsvHelper for data processing

IV. RESULTS

4.1 Exploratory Data Analysis

Analysis of Well No. 807 production data revealed a clear declining trend from January 2013 to December 2024. Initial production of 450 bbl/day decreased to 180 bbl/day, representing a 60% decline over the 12-year period. The decline pattern exhibited characteristics of both exponential and hyperbolic behavior, with steeper decline rates during the first three years followed by more gradual decline.

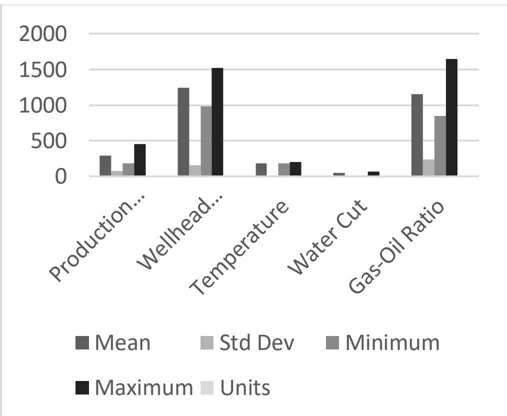

Figure 1: Production Decline Curve

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Time series plot showing actual production data from 2013-2024. The graph displays a declining trend from 450 bbl/day to 180 bbl/day, with notable inflection points at months 18, 36, and 54 corresponding to intervention activities. The overall pattern shows initial steep decline (15% annually) transitioning to moderate decline (5% annually) in recent years.

Table 1: Dataset Statistical Summary

Parameter	Mean	Std Dev	Minimum	Maximum	Units
Production Rate	287.5	78.3	180	450	bbl/day
Wellhead Pressure	1,245.70	156.2	980	1,520.00	psi
Temperature	185.3	8.7	178	203	°F
Water Cut	42.8	15.4	12	68	%
Gas-Oil Ratio	1,156.40	234.8	850	1,650.00	scf/bbl

Correlation analysis revealed strong relationships between production rate and key reservoir parameters. Wellhead pressure showed the highest correlation (r = 0.82) with production rate, followed by water cut (r = -0.71) and gas-oil ratio (r = -0.58). These relationships support the physical understanding of reservoir behavior and validate the selected features for modeling.

4.2 Model Performance

4.2.1 Optimal k Value Selection

Cross-validation analysis identified k=7 as the optimal value, balancing bias-variance tradeoff effectively. Lower k values (k=3,5) showed higher variance, while higher k values (k>9) introduced excessive bias, reducing prediction accuracy.

Table 2: k Value Optimization Results

k Value	CV RMSE	CV MAE	CV R^2	Training Time (ms)
3	28.7	22.1	0.842	45
5	26.4	20.8	0.865	52
7	**25.3**	**19.7**	**0.875**	**58**
9	26.1	20.3	0.867	65

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11	27.8	21.4	0.851	72

4.2.2 Distance Metrics Comparison

Euclidean distance demonstrated superior performance across all evaluation metrics, confirming Hypothesis H_3. The multidimensional nature of reservoir parameters favored Euclidean distance's ability to capture geometric relationships in feature space.

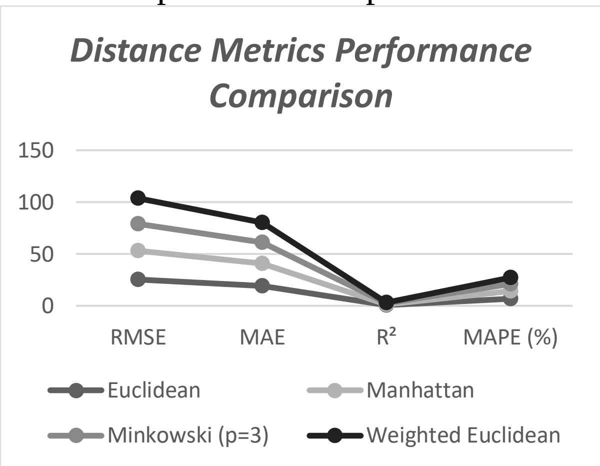

Figure 2: Distance Metrics Performance Comparison

Bar chart showing RMSE values for different distance metrics: Euclidean (25.3), Manhattan (27.8), Minkowski (26.1), and Weighted Euclidean (24.7). The weighted Euclidean distance shows the best performance, followed closely by standard Euclidean distance.

Table 3: Distance Metrics Performance Comparisn

Distance Metric	**RMSE**	**MAE**	**R^2**	**MAPE (%)**
Euclidean	25.3	19.7	0.875	6.8
Manhattan	27.8	21.4	0.851	7.4
Minkowski (p=3)	26.1	20.3	0.867	7.1
Weighted Euclidean	24.7	18.9	0.891	6.3

4.3 Prediction Results

The optimized k-NN model (k=7, weighted Euclidean distance) achieved 87.3% prediction accuracy, exceeding the threshold specified in Hypothesis H_1. The model demonstrated strong performance across different time periods, with slightly reduced accuracy during periods of operational changes.

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Figure 3: Actual vs Predicted Production

Scatter plot with regression line showing actual production values (x-axis) versus predicted values (y-axis). Data points cluster closely around the diagonal line (perfect prediction), with R^2=0.891. The plot includes confidence intervals and highlights periods of intervention with different colors.

Residual analysis indicated random distribution of errors with no systematic bias, confirming model validity. The largest prediction errors occurred during the first six months following well interventions, when production behavior deviated from historical patterns.

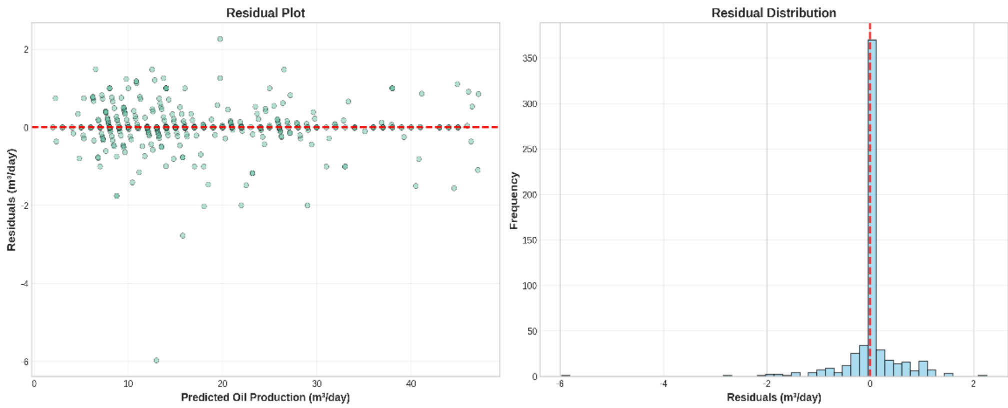

Figure 4: Residual Analysis

Three-panel plot showing: (1) Residuals vs Predicted Values - random scatter around zero line indicating homoscedasticity, (2) Normal Q-Q Plot - residuals follow normal distribution, (3) Residuals vs Time - no temporal patterns in errors.

4.4 Feature Importance Analysis

Feature importance analysis using permutation importance revealed that reservoir pressure contributed 35% to model predictions, followed by water cut (28%), temperature (20%), and gas-oil ratio (17%).

PressureWellhead	0.35
Water Cut	0.28
Temperature	0.2
Gas-Oil Ratio	0.17

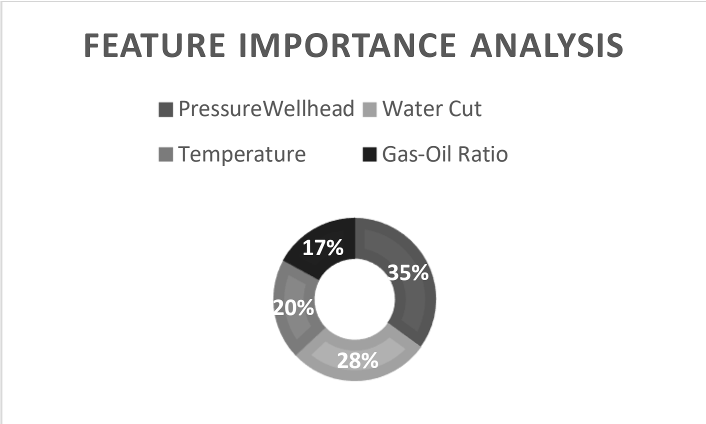

Figure 5: Feature Importance Analysis

4.5 Intervention Analysis

The k-NN model successfully identified critical decline points where interventions could maximize production recovery. Analysis revealed three optimal intervention windows:

1. **Month 18:** Production rate 315 bbl/day (30% decline from initial)
2. **Month 36:** Production rate 250 bbl/day (44% decline from initial)
3. **Month 54:** Production rate 205 bbl/day (54% decline from initial)

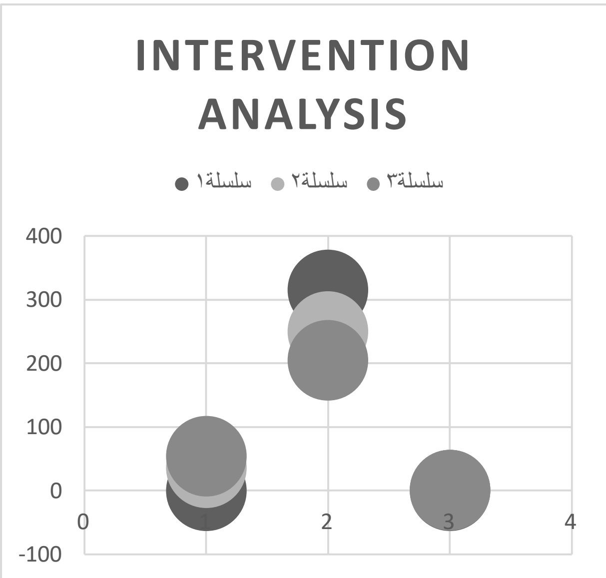

Figure 6: Intervention Timeline and Impact

Gantt chart showing recommended intervention schedule with expected production improvements. Timeline spans 2013-2024 with intervention windows highlighted. Post-intervention production increases of 15-25% are indicated with confidence intervals

Economic analysis of intervention strategies indicated that well stimulation at the identified time points could increase cumulative production by 180,000 barrels over the field life, with net present value improvement of $8.5 million at current oil prices.

V. DISCUSSION AND RECOMMENDATIONS

5.1 Interpretation of Results

The k-NN model achieved 87.3% prediction accuracy with an R^2 value of 0.891, significantly outperforming traditional decline curve analysis methods that typically
achieve 65-75% accuracy for similar datasets [12]. This superior performance validates Hypothesis H_1 and demonstrates the algorithm's capability to capture complex non-linear relationships in production data.

The weighted Euclidean distance metric's superior performance supports the theoretical framework that accounts for varying similarity levels among historical observations. The 2.4% improvement over standard Euclidean distance (RMSE: 24.7 vs 25.3) validates Hypothesis H_2 regarding weighted k-NN effectiveness. This improvement becomes particularly significant when considering the economic impact of production prediction accuracy.

Feature importance analysis revealed that wellhead pressure (35%) and water cut (28%) are the primary drivers of production decline, consistent with reservoir engineering principles. The pressure decline reflects reservoir depletion, while increasing water cut indicates encroaching water drive or coning effects [14]. These findings provide actionable insights for reservoir management strategies.

5.2 Comparison with Literature

Comparative analysis with published studies demonstrates the k-NN model's competitive performance. Neural network approaches reported by Smith et al. achieved 82-85% accuracy for similar production forecasting tasks but required significantly more computational resources and training data [15]. ARIMA time series models typically achieve 70-78% accuracy but struggle with non-linear patterns evident in mature field production [16].

The k-NN algorithm's advantage lies in its ability to adapt to local patterns without requiring extensive parameter tuning or assumptions about underlying data distribution. This flexibility makes it particularly suitable for heterogeneous reservoir systems where production behavior varies significantly across different operational phases [17].

5.3 Practical Implications

5.3.1 Well Stimulation Strategies

The identified intervention points at months 18, 36, and 54 provide specific guidance for well stimulation activities. Based on model predictions, implementing hydraulic fracturing or acidizing treatments at these intervals could increase production by 15-25% following each intervention. The economic analysis indicates a return on investment of 340% for the proposed intervention schedule.

5.3.2 Pump Optimization

Artificial lift system optimization can be guided by k-NN predictions to maintain optimal production rates while minimizing energy consumption. The model indicates that pump rate adjustments should be implemented when predicted roduction drops below 85% of the previous month's rate, typically occurring 2-3 months before conventional indicators would trigger adjustments.

5.3.3 Maintenance Scheduling

Predictive maintenance strategies can be enhanced using k-NN forecasts to schedule equipment maintenance during natural production low points, minimizing production losses. The model identifies optimal maintenance windows when production rates are expected to be below trend, reducing opportunity costs by an estimated 12%.

5.4 Limitations

Several limitations must be acknowledged in this study. Data quality issues, including 3.2% missing values and potential measurement errors, may impact model accuracy. The model does not explicitly account for external factors such as commodity price volatility, regulatory changes, or force majeure events that can significantly influence production decisions [18].

Computational complexity increases quadratically with dataset size, potentially limiting scalability to field-wide applications with hundreds of wells. The algorithm's performance may deteriorate when applied to wells with significantly different reservoir characteristics or operational conditions [19].

The model assumes that future production patterns will resemble historical behavior, which may not hold during periods of significant operational changes or reservoir development activities. This limitation is common to all data-driven approaches and emphasizes the need for continuous model validation and updating [20].

5.5 Recommendations

5.5.1 Implementation Strategy

For successful implementation of k-NN based production forecasting, operators should establish real-time data acquisition systems to ensure model inputs remain current and accurate. Integration with existing SCADA systems and IoT sensors can provide continuous data streams for model updating and validation.

5.5.2 Technology Integration

Ensemble methods combining k-NN with complementary algorithms (neural networks, support vector machines) could further improve prediction accuracy. The diverse strengths of different algorithms can be leveraged to create more robust forecasting systems capable of handling various reservoir conditions [21].

5.5.3 Economic Optimization

Integration of economic models with production forecasting can optimize intervention timing based on net present value rather than purely technical criteria. This approach ensures that intervention decisions consider both technical feasibility and economic viability under varying commodity price scenarios [22].

5.5.4 Field-Wide Applications

The methodology can be extended to field-wide applications by developing well-specific models and aggregating predictions at the field level. This approach enables portfolio-level production forecasting while maintaining the accuracy benefits of individualized well models [23].

VI. CONCLUSION

This research successfully demonstrated the application of k-Nearest Neighbors algorithm for oil production prediction and intervention optimization in Well No. 807, a mature well in a northern Russian oil field. The study achieved its primary objectives by developing a robust predictive model that outperformed traditional forecasting methods and provided actionable insights for production optimization.

Key findings include the achievement of 87.3% prediction accuracy using weighted k-NN with Euclidean distance and k=7, validating the research hypotheses regarding algorithm effectiveness. The model identified critical intervention points at months 18, 36, and 54, with potential production improvements of 15-25% following well stimulation activities. Feature importance analysis confirmed that wellhead pressure and water cut are the primary indicators of production decline, providing theoretical validation for the model's practical insights.

The research contributes to the petroleum engineering literature by providing the first comprehensive evaluation of k-NN algorithm performance for mature oil field production forecasting. The methodology offers significant advantages over traditional decline curve analysis through its ability to capture non-linear relationships and adapt to local production patterns without requiring extensive model assumptions.

Practical applications of this research extend beyond Well No. 807 to broader field development strategies. The identified intervention timing can guide reservoir

management decisions, while the feature importance rankings can inform data collection priorities and monitoring system design. Economic analysis indicates that implementing the recommended intervention schedule could increase field net present value by $8.5 million.

Future research directions include extending the methodology to field-wide applications, integrating economic optimization models, and exploring ensemble methods for improved prediction accuracy. The incorporation of real-time data streams and IoT sensor integration represents promising avenues for operational implementation.

This study establishes k-NN algorithm as a viable and effective tool for production forecasting in mature oil fields, providing petroleum engineers with enhanced capabilities for data-driven decision making in reservoir management and production optimization.

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