



# The Development, Application and Prospect of Oil and Gas Production Forecasting Technologys

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## ABSTRACT

In the practice of oil and gas field development, the heterogeneity of reservoir physical properties, the dynamic changes of fluid properties, and the diversity of process measures constitute a complex development environment. This complexity makes the analysis of oil and gas production data highly dependent on the professional experience of petroleum scientists and engineers. Traditional analysis methods not only consume a lot of computing resources and time costs, but also are difficult to meet the needs of efficient development of modern oil and gas reservoirs. Therefore, it is urgent to explore more efficient production forecasting methods. In recent years, with the rise of machine learning technologies such as deep neural networks and random forest algorithms, with their significant advantages in high - dimensional data processing, time - series feature capture, and development data feature mining, they have achieved fruitful results in the field of oil and gas production forecasting. This paper systematically combs the evolution context of oil and gas production forecasting technology, elaborates the principles, advantages and disadvantages of mainstream machine learning methods, summarizes the application status of machine learning methods in the field of oil and gas production forecasting, analyzes the potential problems in the application process, and looks forward to the future development trend. The study points out that in the future, we should focus on promoting two technological breakthroughs: first, organically integrating the physical mechanism of the reservoir with the machine learning model to enhance the interpretability of the model and ensure the reliability of the prediction results; second, developing algorithms and transfer learning technologies suitable for small sample scenarios to deeply tap the value of historical production data and provide more accurate and efficient technical support for oil and gas production forecasting.

## KEYWORDS

Oil and gas production forecast; Machine learning; Deep learning.

## 1. INTRODUCTION

Oil and gas resources are the lifeblood of national economic development and the strategic cornerstone for maintaining social stability and national security [1,2]. With China's oil and gas production exceeding 400 million tons of oil equivalent for the first time in 2024, maintaining a growth of 10 million tons for 8 consecutive years, and the increasing proportion of unconventional oil and gas resources (such as shale oil, shale gas, coalbed methane, etc.) in the total production, traditional production forecasting methods are facing unprecedented challenges. As one of the core technologies of oilfield development engineering, oil and gas production forecasting plays a vital role in the whole life cycle of oilfield management. Accurate production forecasting is not only the basis for formulating development plans and optimizing production parameters, but also the key basis for evaluating the economic value of oil and gas fields and planning investment strategies.

Production forecasting technology can be traced back to the middle of the 20th century, initially relying mainly on simple empirical formulas and decline curve analysis. With the development of computer technology, numerical simulation methods gradually became the mainstream of production forecasting, which can consider more geological and engineering parameters. After entering the 21st century, machine learning methods began to be applied in the field of production forecasting, and the breakthrough of deep learning technology in recent years has provided a new idea for solving the production forecasting problem in unconventional oil and gas and complex scenarios. At present, oil and gas production forecasting technology is in a critical period of transformation from traditional empirical models to data - driven intelligent models.

The purpose of this paper is to systematically comb the development context of oil and gas production forecasting technology, compare and analyze the advantages and disadvantages and application scenarios of various methods, pay special attention to the innovative application of artificial intelligence technology in production forecasting, and put forward prospects for future research directions. The full text will successively introduce traditional production forecasting methods, machine learning methods, deep learning methods, and cutting - edge technologies of multidisciplinary integration, and finally summarize the current challenges and development trends to provide a comprehensive technical reference for oilfield scientific research personnel.

## **2. TRADITIONAL OIL AND GAS PRODUCTION FORECASTING METHODS**

Traditional oil and gas production forecasting methods are mainly based on mathematical statistics principles and reservoir engineering theories, forming the basis of the production forecasting technology system, and these methods have accumulated rich application experience in conventional oil and gas field development. According to the different prediction principles and application scenarios, they can be divided into three categories: empirical formula method, decline curve analysis method and material balance method, each of which has its own applicable conditions and limitations.

### **2.1. Empirical Formulas and Statistical Models**

The empirical formula method is the main means of early oil and gas production forecasting, and makes predictions through mathematical relationships summarized by observing a large number of oil and gas field production data, among which the most representative is the Arps decline curve. In 2007, Rushing [3] combined the Arps decline model with numerical simulation analysis, used the Arps rate - time equation to evaluate the simulated production in a specific period of the well's production life, and compared the estimated reserves with the true values. In 2008, when Ilk et al. [4] studied the hyperbolic rate decline relationship, they found that the production data of shale gas wells showed a new "Power - Law Exponent (PLE)" rate relationship, so they established the PLE regression analysis method. Experiments have proved that it is more widely applied than the hyperbolic rate decline relationship. In 2010, Duong et al. [5] proposed the Duong production decline model, which was applied to shale gas prediction. In the same year, Valkol et al. developed the Stretch Exponential Production Decline (SEPD) model for shale gas production, and empirical evidence showed that the fitting effect was also good. In 2011, Clark et al. [5] added a multiplication factor to the exponential growth equation to develop the Logistic growth model (LGM), and discussed its applicability by combining the model with actual production [6]. The advantage of this kind of method is that it is simple to calculate, has few parameters and is easy to implement, and is especially suitable for the early production forecasting of new development oilfields with limited data.

The Weibull model is another important statistical prediction method, proposed by Chen Yuanqian and Hu Jianguo in 1995. By introducing shape parameters and scale parameters, it can better describe the production change characteristics of oil and gas fields in different development stages [7]. The

mathematical form of the Weibull model is flexible, and various decline modes can be simulated by adjusting parameters, so it performs well in the prediction of the middle and late development stages of conventional oil and gas fields. However, this kind of statistical model is essentially a "black box" model, lacks physical mechanism support, and has poor adaptability to the complex production dynamics of unconventional oil and gas fields.

## **2.2. Decline Curve Analysis Method**

Decline Curve Analysis (DCA) is the most commonly used production forecasting technology in the middle and late stages of oil and gas field development, and its core idea is to predict future production by fitting the historical production decline law. According to whether the decline rate changes, it can be divided into three basic types: exponential decline, hyperbolic decline and harmonic decline. In 2008, Gao Wenjun proposed the theoretical basis of the double logarithmic water drive characteristic curve, expanding the application range of the traditional decline curve in water drive development oilfields [8]. In the probabilistic DCA method, analysts will select a model that best matches the actual data. However, there are often multiple models that may fit the data almost perfectly, and these best-fitting models may not best represent the flow characteristics. Therefore, in 2019, Hong [9] used the Bayesian method to integrate model uncertainty into the probabilistic DCA method in unconventional oilfield mining, mainly studying four models: Arps, SEM, LGM and PanCRM, indicating that PanCRM is more likely to well describe unconventional flow behavior.

As a common technology for estimating remaining proved reserves, the traditional Decline Curve Analysis (DCA) method has obvious limitations in application. Although this method can predict future production or ultimate recoverable reserves based on a large amount of historical production data, its applicability is restricted by the following: first, for new development blocks with incomplete data or oilfields in the early development stage, due to the lack of sufficient dynamic production data, the DCA method is difficult to be effectively applied; second, this method is mainly suitable for oil and gas wells whose production has entered the decline stage, but performs poorly in the prediction of the whole life cycle of the oilfield (including production construction period, stable production period, etc.); more importantly, the traditional DCA method adopts a static analysis mode, which fails to fully consider the time series correlation and dynamic change characteristics between production data, resulting in limited prediction accuracy [10,11].

## **2.3. Material Balance and Numerical Simulation Methods**

The material balance method is based on the principle of mass conservation of the oil and gas reservoir, and predicts future dynamics by establishing the relationship between the underground fluid volume and the surface production. In 1995, Ji Bingyu derived the hyperbolic, harmonic and exponential production decline equations from the relative permeability curve and the material balance principle, providing theoretical support for the decline curve [12]. The advantage of the material balance method is that it has a clear physical meaning and can reflect the energy change and driving mechanism of the reservoir. However, its disadvantage is that it assumes that the reservoir is homogeneous, while the actual reservoir is mostly heterogeneous, and the prediction accuracy is affected.

The numerical simulation method is the most complex and closest to the actual one among the traditional prediction technologies, and simulates the dynamic of the oil and gas reservoir by solving the mass, momentum and energy conservation equations. Numerical simulation can consider complex geological conditions, a variety of driving mechanisms and development methods, and theoretically can provide the most accurate production forecast. However, this method has high calculation cost, long modeling cycle, and extremely high requirements for data quality and personnel professional level. For unconventional oil and gas reservoirs, due to the existence of nano - scale pore structures

and complex flow mechanisms, the applicability of traditional numerical simulation methods faces challenges.

**Table 1** Comparison of Traditional Oil and Gas Production Forecasting Methods

Method Category	Representative Model	Advantages	Limitations	Application Scenario
Empirical Formula Method	Arps Decline Curve, Gompertz Model, Weibull Model	Simple calculation, few parameters, convenient implementation	Lack of physical mechanism, poor adaptability	Early development of conventional oil and gas fields
Decline Curve Method	Exponential, Hyperbolic, Harmonic Decline Curves	Only need production data, intuitive results	Cannot reflect development adjustments, poor applicability to unconventional	Middle and late development of oil and gas fields
Material Balance Method	Reservoir Material Balance Equation	Clear physical meaning, reflecting energy changes	Assume homogeneous reservoir, poor adaptability to heterogeneous	Closed conventional reservoir
Numerical Simulation Method	Black Oil Model, Component Model	Closest to reality, can simulate complex conditions	High calculation cost, long modeling cycle	Large conventional oil and gas fields

Although traditional production forecasting methods have played an important role in the development of conventional oil and gas fields, with the extension of exploration and development objects to complex fields such as unconventional, low permeability and deep layers, the limitations of these methods have become increasingly prominent. The main challenges of traditional methods come from three aspects: ①poor data adaptability, difficult to handle the complex production dynamics and nonlinear relationships of unconventional oil and gas fields; ②weak multi-source information integration ability, unable to effectively use multi-dimensional data such as geological, engineering and production; ③lack of real-time update mechanism, difficult to reflect the impact of development adjustments and production system changes in a timely manner. These challenges have promoted the development of production forecasting to machine learning and deep learning, bringing revolutionary changes to oil and gas production forecasting.

### 3. APPLICATION OF MACHINE LEARNING IN OIL AND GAS PRODUCTION FORECASTING

With the rapid development of big data technology and computing power, machine learning methods have made remarkable progress in the field of oil and gas production forecasting, providing new ideas for solving the challenges faced by traditional methods. Machine learning algorithms can

automatically learn complex patterns from massive data and handle nonlinear relationships. Compared with traditional methods, machine learning technology has three core advantages: ①powerful nonlinear modeling ability, which can capture the complex relationship between production and various influencing factors; ②excellent multi-source data integration ability, which can simultaneously process geological information such as logging, seismic, fracturing parameters and production data; ③good adaptive learning ability, and the model performance can be continuously improved with the continuous input of new data. These characteristics make machine learning methods particularly suitable for solving complex problems in unconventional oil and gas production forecasting.

### 3.1. Traditional Neural Network Models

Typical machine learning algorithms include: Random Forest (Random Forest) for feature selection and production interval prediction; Support Vector Regression (SVR) for handling small sample high-dimensional problems; Gradient Boosting Decision Tree (GBDT) for integrating various engineering parameters for production prediction; and Artificial Neural Network (ANN) for establishing complex mapping relationships between input parameters and production. These algorithms have their own focuses and can be flexibly selected according to specific prediction scenarios.

As the earliest machine learning model applied to production forecasting, BP neural network adjusts the network weights through the error backpropagation algorithm, and can approximate any nonlinear function. In 2005, Xing Minghai [13] and others applied the fuzzy neural network to the prediction of oilfield production, and the experiment proved that the fuzzy neural network had higher prediction accuracy than the BP neural network. In 2011, Lü Yumin et al. [14] established a prediction model of the ratio of monthly production to cumulative production based on the BP neural network, and carried out dynamic prediction of gas well production based on this. In 2014, Genetic Algorithm (GA) and Support Vector Machine (SVM) algorithms were widely used in the petroleum and natural gas industry. In 2016, Tian Yapeng [15] and others improved the BP neural network based on the genetic algorithm, used the improved model to predict the shale gas production, and discussed the applicability of the BP neural network model. Neural Network (NN) can process nonlinear data sets and is used in production forecasting [16], but NN has disadvantages in solving time series data. The information transmission in this model is only forward, and past data cannot be recorded, while Recurrent Neural Network (RNN) can handle long-term dependency problems and is widely used in oil well production forecasting [17,19].

However, the traditional BP neural network has obvious limitations: the network structure design depends on experience, and it is easy to fall into local optimality; the processing ability of time series data is limited, and it is unable to effectively capture the time series dependency of production changes. These shortcomings limit the further application of BP neural network in production forecasting.

### 3.2. Combination Models

Combined prediction models often obtain more robust prediction effects by integrating the advantages of multiple single models. In 2012, Tang Lifang et al. [20] used system dynamics and grey correlation model, CPSO - SVM model to predict oil demand [21]. In 2013, Sun Mei [22] used neural network and Kalman algorithm to predict oil demand. In the same year, Zhang Fangzhou [23] and others proposed to use weighted combination of grey prediction and BP neural network to predict production. This improved model can solve the problem of insufficient training data set and help optimize model parameters, but it is difficult to determine the weight of the model due to the lack of theoretical guidance for the weight. In 2016, Li Zhenyu et al. [24] predicted oil demand using factor analysis and Logistic model. In 2017, Xiang Yunfei et al. [25] used the combination of multiple linear regression and RBF neural network to predict oil well parameters, and the effect was better than that

of a single model. In 2019, Wang Yong [26] proposed a combined model of SEPD and Duong models. In the production stage, the Duong model is used to predict the first half of the production decline part, and the latter part of the production decline is predicted by the weighted combination of the SEPD model and the Duong model. The results show that the combined prediction effect is better. In 2020, Zheng Minggui et al. [27] combined grey correlation analysis with ARIMA - BP neural network combined model, indicating that the combination of linear model under statistics and nonlinear model in machine learning has higher prediction accuracy than single model. In 2021, Fan et al. [28] proposed an error correction combined model combining ARIMA and LSTM models. ARIMA predicts the linear part, and then LSTM is used to correct the prediction residual of ARIMA. The results show that this correction model has higher prediction accuracy and better effect than the single model, and has universal applicability to oil and gas wells.

**Table 2** Comparison of Applications of Machine Learning Methods in Oil and Gas Production Forecasting

Method Category	Representative Algorithm	Advantages	Limitations	Application Scenario
Traditional Neural Network	BP Neural Network, RBF Neural Network	Strong nonlinear modeling ability	Easy to fall into local optimality, poor time series processing	Static production forecasting
Integrated Learning Method	Random Forest, GBDT	Anti - overfitting, feature importance analysis	Limited adaptability to time series	Multi-factor production forecasting
Support Vector Machine	SVR, LS - SVM	Good performance in small samples, complete theory	Difficult kernel function selection, large calculation amount	Limited data scenarios
Combination Model	Weighted Average, Stacking	Robust prediction, error complementarity	High model complexity, poor interpretability	Comprehensive prediction tasks
Optimization Algorithm	Genetic Algorithm, Particle Swarm Algorithm	Global search, automatic parameter tuning	High calculation cost, possible premature convergence	Model parameter optimization

Although machine learning methods have made remarkable progress, they still face some challenges: first, they are highly dependent on high - quality labeled data, while oil and gas field development data often have noise and missing; second, the model interpretability is insufficient, which is difficult to provide transparent basis for engineering decisions; third, the real-time prediction and adaptive update mechanism need to be improved. These challenges have promoted the exploration and

application of deep learning technology in production forecasting, creating a new era of intelligent forecasting.

## **4. APPLICATION OF DEEP LEARNING IN OIL AND GAS PRODUCTION FORECASTING**

As an important branch of machine learning, deep learning can automatically learn the hierarchical features of data by constructing a multi-layer nonlinear network structure, and has achieved revolutionary success in image recognition, natural language processing, time series prediction and other fields. In recent years, deep learning technology has been introduced into the field of oil and gas production forecasting, providing a new solution for solving the complex dynamic forecasting problem of unconventional oil and gas reservoirs. This part will deeply analyze the innovative application of deep learning models in production forecasting, focus on the technical characteristics and actual effects of advanced architectures such as Long Short - Term Memory Network (LSTM) and Convolutional Neural Network (CNN), and look forward to the integration trend of deep learning and physical models.

The essential difference between deep learning and traditional machine learning lies in its feature learning ability. Traditional machine learning relies on manually designed features, while deep learning can automatically extract the multi-level abstract features of data through multi-layer networks. This characteristic makes it particularly suitable for dealing with complex spatio - temporal correlation problems in oil and gas production, such as the relationship between fracturing fracture networks and production dynamics, and the effect of reservoir heterogeneity and interwell interference.

### **4.1. Time Series Forecasting**

Oil and gas production is essentially time series data, which is affected by many factors such as reservoir characteristics, development history and engineering measures, and has long-term dependence and nonlinear dynamic characteristics. Traditional methods are difficult to effectively capture these complex time patterns, while specially designed Recurrent Neural Networks (RNNs) and their variants can memorize historical information and use it for current prediction. In 2020, Gu Jianwei et al. [29] first applied the Long Short-Term Memory Neural Network (LSTM) to production forecasting, solved the problem of gradient disappearance of the traditional RNN, and realized the time series modeling with long-term memory ability. In 2021, Fan et al. [30] proposed an error correction combined model combining ARIMA and LSTM models. ARIMA predicts the linear part, and then LSTM is used to correct the prediction residual of ARIMA. The results show that this correction model has higher prediction accuracy and better effect than the single model, and has universal applicability to oil and gas wells. Li et al. [31] used the LSTM network model to carry out feature extraction and long-time series dependency learning on dynamic production curve data, effectively discovered the main control factors of different types of gas fields, and realized the accurate prediction of production in different gas fields.

Diversified neural network architectures provide flexible choices for different prediction scenarios. In addition to LSTM, other deep learning models such as Gated Recurrent Unit (GRU), Temporal Convolutional Network (TCN) and Transformer have also been gradually applied to production forecasting. These models have their own advantages: GRU has a simpler structure and high training efficiency; TCN captures multi-scale time series patterns through dilated convolution; Transformer uses self-attention mechanism to model global dependency. Diverse network construction methods can meet the refined prediction needs in different scenarios.

## 4.2. Convolutional Neural Networks and Spatiotemporal Feature Learning

The application of Convolutional Neural Network (CNN) in production forecasting has opened up a new technical path. Different from the traditional time series model, CNN automatically learns local spatial features through convolution kernels, which is particularly suitable for dealing with production forecasting problems with spatial correlation, such as interwell interference analysis and regional production forecasting. The hybrid model combining CNN and LSTM can capture spatiotemporal features at the same time, and has performed well in shale gas well production forecasting.

Graph Neural Network (GNN) is another emerging deep learning method that processes graph structure data through a message passing mechanism. In production forecasting, GNN can represent the oil and gas field as a graph structure, where nodes represent production wells and edges represent interwell relationships, and predictions are made by learning the features of nodes and edges. This method can explicitly model interwell interference and reservoir connectivity, providing new ideas for overall oilfield development optimization. Huang et al. [32] established a GNN - LSTM model to realize production forecasting under various well control scenarios, characterized the connections between different production wells through the GNN model, and simulated the evolution of the constructed GNN model over time through the LSTM structure. Du et al. [33] fully considered the impact of interwell interference on production, established a hybrid model based on deep learning (GCN - LSTM), established a Graph Convolutional Network (GCN) based on GNNs to capture the complex spatial patterns between well groups, used the Long Short - Term Memory (LSTM) neural network to extract complex time correlations from historical production data, effectively captured spatiotemporal correlations, and realized fast and accurate prediction of oil production.

Deep reinforcement learning combines prediction and decision-making. By defining appropriate reward functions, the model can not only predict production but also recommend optimization measures. This closed-loop decision-making mode represents the future development direction of production forecasting technology.

## 4.3. Physical Information Fusion and Interpretability Improvement

Physically constrained deep learning is a current research hotspot, which aims to integrate reservoir engineering knowledge into the design of neural networks to improve the physical rationality and extrapolation ability of the model. The methods include: adding material balance constraints to the loss function; designing physically guided network architectures; using differential equations as regular terms, etc. This fusion method not only maintains the flexibility of data-driven, but also follows the basic physical laws, making the prediction results more credible.

Model interpretability techniques help understand the decision basis of deep learning models. Techniques such as SHAP values, LIME, and attention mechanisms can reveal the influence degree of different input features on the prediction results, for example, identifying which fracturing parameters are most critical to the production of shale gas wells [34,35]. The improvement of interpretability not only increases the trust of engineers in the model, but also can guide the optimization of field operation parameters.

The real - time prediction and adaptive update mechanism enables the deep learning model to continue to evolve. Through online learning technology, the model can automatically adjust parameters with the continuous inflow of new production data to adapt to the dynamic changes of the reservoir. This ability is particularly important for unconventional oil and gas fields, because their production dynamics are often difficult to accurately describe with fixed models.

**Table 3** Innovative Applications of Deep Learning Models in Oil and Gas Production Forecasting

Model Type	Technical Characteristics	Advantages	Application Scenario	Typical Case
DLSTM	Multi-layer LSTM stacking, gating mechanism, Dropout regularization	Capture long-term dependencies, prevent overfitting	Single well production time series forecasting	Tight oil production forecasting
CNN - LSTM	Convolutional layer extracts spatial features, LSTM processes time series	Model spatiotemporal correlation at the same time	Multi-well interference analysis	Shale gas well group forecasting
Graph Neural Network	Message passing, node and edge feature learning	Explicit modeling of interwell relationships	Overall oilfield development optimization	Block production forecasting
Physically Constrained Model	Integrate physical knowledge such as mass conservation and flow equations	Physically reasonable, strong extrapolation ability	Complex mechanism scenarios	Low permeability reservoir forecasting
Deep Reinforcement Learning	State-action-reward framework, closed-loop decision-making	Prediction-optimization integration	Real-time production optimization	Intelligent parameter adjustment system

## 5. TECHNICAL CHALLENGES AND DEVELOPMENT DIRECTIONS

Although deep learning has shown great potential in production forecasting, it still faces several technical challenges. The main bottleneck is the insufficient data quality and labeling, especially for newly developed oilfields, which lack enough historical data for training. The high calculation cost of the model also limits its deployment in real - time applications, especially for three - dimensional reservoir scale prediction problems. In addition, how to balance model complexity and interpretability still needs in - depth exploration.

Future development directions include: strengthening interdisciplinary theoretical and technical research to promote the deep integration of artificial intelligence and reservoir engineering; exploring small sample learning, transfer learning and other technologies to solve the problem of insufficient data; developing edge computing frameworks to achieve real - time prediction; building an open benchmark testing platform to promote algorithm comparison and progress. In the future, intelligent oil and gas production forecasting technology can carry out in - depth research in real - time prediction and optimization, data fusion and enhancement, physical constraints and interpretation, and model update and adaptation.

Deep learning has brought a paradigm change to oil and gas production forecasting, but its industrial application is still in its infancy. Through continuous technological innovation and engineering practice, deep learning is expected to become the core technology of intelligent oil and gas field development, providing strong support for improving recovery efficiency and reducing development costs. The future intelligent prediction system will not only be a production prediction tool, but also an integrated platform integrating prediction, optimization and decision support, promoting the oil and gas industry to accelerate towards digitization and intelligence.

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