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Production Prediction Model of Tight Gas Well Based on Neural Network Driven by Decline Curve and Data

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Abstract: The accurate prediction of gas well production is one of the key factors affecting the economical and efficient development of tight gas wells. The traditional oil and gas well production prediction method assumes strict conditions and has a low prediction accuracy in actual field applications. At present, intelligent algorithms based on big data have been applied in oil and gas well production prediction, but there are still some limitations. Only learning from data leads to the poor generalization ability and anti-interference ability of prediction models. To solve this problem, a production prediction method of tight gas wells based on the decline curve and data-driven neural network is established in this paper. Based on the actual production data of fractured horizontal wells in three tight gas reservoirs in the Ordos Basin, the prediction effect of the Arps decline curve model, the SPED decline curve model, the MFF decline curve model, and the combination of the decline curve and data-driven neural network model is compared and analyzed. The results of the case analysis show that the MFF model and the combined data-driven model have the highest accuracy, the average absolute percentage error is 14.11%, and the root-mean-square error is 1.491, which provides a new method for the production prediction of tight gas wells in the Ordos Basin.

Keywords: decline curve; neural network; yield prediction; dense gas wells

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1. Introduction

With the intensification of the contradiction between the oil and gas supply and demand, accelerating the development of oil and gas fields has attracted more and more attention, and the production prediction is of great significance to the efficient development of oil and gas fields. Predecessors have carried out a lot of research on oil and gas well production prediction, including traditional tight gas well production prediction methods, such as the Arps decline curve method, analytical model method, semi-analytical model method, and numerical simulation method. J. J. Arps has proposed the Arps decline curve in 1945, which is widely used in the field of petroleum engineering. Based on the empirical formula, the Arps decline curve describes the attenuation model of oil and gas well production with time, including the exponential decline, hyperbolic decline, and harmonic decline model. The Arps decline model has been verified by a large number of domestic and foreign scholars to not be suitable for the production prediction of unconventional oil and gas fields. The representative scholars in this field are Volk [1], HongYuan [2], Duong [3], Lee [4], and Kabir [5]. The production equation is derived based on the steady-state seepage theory and the principle of material balance. We fit the production data through the chart, such as the Fetkovich method [6], Agarwal–Gardner method [7], and Blasingame method [8]. The semi-analytical method is mainly based on the linear flow hypothesis. This method can effectively describe the seam mesh reconstruction, and it is convenient for calculation, so it has been widely used. The analytical model method and semi-analytical model method are only suitable for the production prediction of single-phase fluid. Because of the serious Guénon linearity of the mathematical model itself, it is not suitable for gas–water two-phase flow in the process of tight gas development. The numerical simulation method establishes the numerical model of a single well or gas reservoir through numerical simulation software, and predicts the production performance of a single well or gas reservoir based on history fitting. Many scholars have established a mechanical production prediction model for tight gas wells based on the dual porosity model put forward by Warren and Root [9] in 1963. The dual porosity model assumes that fractured reservoirs are composed of uniformly distributed matrix systems and natural fracture systems. Representative scholars are Sun Ruofan et al. [10], Xiao Zunrong et al. [11], Luo Erhui et al. [12], Larsen et al. [13], Raghavan [14], Ozkan et al. [15], Yao Jun et al. [16], Su Yuliang et al. [17], and Ren Zongxiao et al. [18].

The production prediction methods established by scholars in the past have strongly promoted the development of tight gas well production prediction models, but the above models are all based on certain assumptions, and there is a big error between the prediction results and the actual production of oil and gas fields. With the development of computer technology and data acquisition technology, machine-learning technology was introduced into the field of oil and gas well production prediction. In 2005, Liao Ruiquan [19] and others used a backpropogation (BP) network model to establish the production prediction model based on geological factors such as porosity, reservoir thickness, fracturing sand volume, sand ratio, and production factors such as working pressure. In 2008, Ni Hongmei [20] and others established a three-layer BP neural network model for yield prediction, but the neural network has the problems of a slow convergence speed and low accuracy. In 2015, Klie [21] and others combined the analysis of the growth model with a data-driven neural network to generate a highly predictive alternative model. After using the physics and flexibility of the growth model to reduce the requirements for the data, the data-driven model is used for correlation correction, which has a high accuracy in medium- and long-term shale gas production prediction. Raphae [22] and others use the prediction algorithm based on big data to compare the actual production data with the forecast data in order to evaluate the production situation in this area. In 2016, Cao [23] proposed a production prediction model for unconventional oil and gas wells based on an artificial neural network. Compared with the decline curve analysis method, this model takes a more comprehensive consideration of geological factors and production factors. The performance of unconventional reservoir production prediction is better than that of the decline curve. Jia [24] and others put forward a method for the automatic history fitting and decline analysis of unconventional oil and gas reservoirs by combining the time-series analysis method and neural network. Compared with the traditional Arps decline curve, this method has a higher accuracy and better fitting effect. After that, many scholars will predict the production of oil and gas wells based on neural networks. The representative scholars are Liu Wei [25] (2020), Gu Jianwei [26] (2020), Ma Xianlin [27] (2021), Han Shan [28] (2022), Cheng Bingjie [29] (2022), and Li Juhua [30] (2023). Although the above scholars have applied a big data approach to the field of tight well production prediction, most of the models are purely data-driven. Although these models are better than the traditional decline model and percolation mechanism model, the generalization ability and anti-interference ability of the model are poor, and the prediction effect is not good in the case of sparse or fluctuating data. And these models do not take into account the physical law of seepage in tight gas reservoirs. In order to overcome the disadvantage of a pure data-driven model's adaptability, PARK [31] proposed a seepage model based on the physical model and mixed data-driven model in 2020. The results show that, even if the amount of data is reduced, the addition of the physical model can still maintain the high accuracy of the hybrid model. In 2022, in order to solve the problem of the pressure prediction of a heterogeneous reservoir, Xue Liang [32] proposed a neural network model driven by percolation physics and data, and added the percolation physical information of the heterogeneous reservoir to the neural network by regularization. In 2022, Xuechen Li [33] proposed a new physically constrained deep-learning framework based on bidirectional gated circulation units (Bi GRU) and deep hybrid neural network (DHNN) combined neural networks (BI GRU-DHNNs) for the long-term production prediction of multiple fractured wells. By considering physics-based dependencies between constraints and production, the Bi GRU-DHNN model significantly improves the accuracy and versatility of the long-term production prediction for fractured wells in a grid-free and efficient manner. In 2024, Hai Wang [34] and others combined the Caputo fractional derivative, automatic differentiation, and sparse regression to propose a physical-information-based neural network (PINN) method for identifying the decline curves of shale gas wells. The PINN was trained on production data from 20 wells in the Duvernay Formation and showed that the decline curve can be accurately described by a non-homogeneous fractional differential equation.

The research of the above two scholars [31,32] shows that the combined use of a physical model and data-driven model can increase the prediction accuracy of the model and improve the generalization ability and anti-interference ability of the pure data-driven model. This paper combines the traditional decline curve model with the neural network of the data-driven model, and embeds the decline curve model into the optimization and adjustment of the data-driven model through driving and stimulating in the process of neural network learning. The prediction effects of three kinds of decline curve models and the prediction effects of three kinds of decline curve models and data-driven models are analyzed, respectively. A tight gas well production prediction model based on the decline curve combined with a data-driven neural network with a high prediction accuracy, generalization ability, and strong anti-interference ability is established, which provides a powerful tool for calculating tight gas well production.

2. Principle of Decline Model

2.1. Principle of Arps Decline Model

The Arps decline model is a method suitable for conventional gas well production decline prediction proposed by J. J. Arps [33]. The production decline rate is defined as:

$$D = -\frac{1}{q(t)}\frac{dq(t)}{dt} \tag{1}$$

The relationship between the output and decline rate is as follows:

$$\frac{D_{\mathrm{i}}}{D} = \left(\frac{q(t)}{q_i}\right)^n \tag{2}$$

where n is the decline index, and the range of values is $0 \leq \mathrm{n} \leq 1$, and the type of production decline depends on the value of n. When n = 0, it is exponentially decreasing:

$$\frac{\mathrm{q(t)}}{q_i} = \frac{1}{e^{D_i t}} \tag{3}$$

When $0 < n < 1$, it is hyperbolic decreasing:

$$\frac{q(t)}{q_i} = \frac{1}{(1 + nD_i t)^{1/n}} \tag{4}$$

When n = 1, it is harmonic decreasing:

$$\frac{q(t)}{q_i} = \frac{1}{1 + D_i \mathrm{t}} \tag{5}$$

where t is the time, n is the decline index, q_{i} and D_i represent the initial production and initial decline rate, and $q(t)$ and D represent the production and decline rate at t moment.

The traditional Arps decline model has been confirmed by a large number of domestic and foreign scholars to not be suitable for the production prediction of unconventional oil and gas wells. Therefore, the performance of this model is not as good as that of other models. This model is often used as a comparative model to highlight the advantages of other models.

2.2. Extension Index (SPED) Model

With the decline of conventional oil and gas production and the increasing demand for oil and gas all over the world, it is imperative that we develop unconventional oil and gas reservoirs. In order to improve the traditional Arps decline model (hyperbolic decline model in the Arps decline model) when it is applied to unconventional oil and gas reservoirs, the prediction results are quite different from the actual ones. Volk [34] applied the extension index decline model to the production decline analysis of shale gas wells and established the extension index (SPED) model.

The expression of output is:

$$q = q_i \exp\left[-\left(\frac{t}{\tau}\right)^{-n}\right] \tag{6}$$

The expression of cumulative output is:

$$N_p = \frac{q_0 \tau}{n}\left\{\Gamma\left[\frac{1}{n}\right] - \Gamma\left[\frac{1}{n}, \left(\frac{1}{n}\right)^{-n}\right]\right\} \tag{7}$$

The decline rate is expressed as follows:

$$D = \frac{n}{t}\left(\frac{t}{\tau}\right)^{n} \tag{8}$$

where n is an exponential parameter and τ is a characteristic time parameter. When n > 0, t is constant. Let $A = (t/\tau)^n$; A gradually increases with time. When t > τ, A > 1; as t goes to infinity, A goes to infinity.

2.3. Principle of Modified Fracture Flow (MFF) Model

The modified fracture flow (MFF) decline model is a new type of oil well performance prediction model (variable coefficient flow model) proposed by HongYuan [2] for unconventional reservoirs. Compared with the SPED model, the application of the modified fracture flow (MFF) decline model in the mathematical calculation is simple, but its prediction results, error analysis, and fitting effect are consistent with or even better than the SPED model.

The formula for calculating oil production per well is as follows:

$$q = q_1 \cdot t^y \tag{9}$$

where y is obtained by fitting the field data. First, assume x to be as follows:

$$x = \frac{\log(q_o/q_{o\max})}{\log(t)} \tag{10}$$

Then, we carry out the relation curve between x and t, and, finally, through logarithmic fitting, the calculation formula of y is as follows:

$$y = a\ln(t) + b \tag{11}$$

In the formula, a and b are the logarithmic fitting coefficients and real numbers.

The formula for calculating the cumulative oil production per well is as follows:

$$Gp = \int_{1}^{t} q_{o\max} \cdot t^{y} dt \tag{12}$$

where Gp represents the cumulative production, $q_{o\max}$ is the maximum flow, t is the time variable, and dt is the small increment of the time variable.

3. Production Prediction Model of Tight Gas Well Based on Decline Model and Data-Driven Neural Network

The traditional BP neural network is good at dealing with the nonlinear relationship between parameters, automatically adjusting the model parameters by learning sample data, and using the trained model to predict the production of tight gas wells in the future. However, the BP neural network may fall into the local minimum rather than the global optimal solution in the training process, and the generalization ability and anti-jamming ability of the network are poor, so the model cannot be well extended to the new data outside the learning samples.

The Arps decline model is a method to predict the oil and gas well production decline with time increasing based on the relationship between the actual oil and gas well decline rate and production. It can assist the BP neural network with a more efficient search to obtain the weight and threshold of the network, so that the neural network can reach a stable state more quickly. The decline model is used to optimize the BP neural network and give full play to their respective strengths to achieve the complementarity of the two, so as to improve the accuracy of the model.

The production prediction model of tight gas wells is established by combining the decline curve model with a data-driven neural network. It is necessary to add the solution obtained by the decline model to the fitting solution of the neural network, and replace the original single fitting loss function with the traditional model and the total data loss function, and the total loss is the sum of two losses:

$$Loss = MSE_{\mathrm{DATA}} + MSE_{\mathrm{DC}} \tag{13}$$

Among them:

MSE_{DATA}—real data and neural network prediction data;

MSE_{DC}—real data and prediction error of decreasing model.

The model is established on the basis of the BP neural network, and the mathematical derivation principle is as follows:

The model error calculation is as follows:

$$E = \frac{1}{2}(d-o)^2 + \frac{1}{2}(DC-o)^2 \tag{14}$$

Among them, E is the value of the error function, d is the expected output, which is the target value in the training data, o is the actual output, which is the predicted value of the neural network, and DC is the target value after uncertainty correction.

We expand the error to the hidden layer to obtain the following:

$$\begin{aligned} E &= \tfrac{1}{2}\left(d - f(net_k)^2\right) + \tfrac{1}{2}\left(DC - f(net_k)^2\right) \\ &= \tfrac{1}{2}\left(d - f\left(\sum W_{jk}y_j\right)^2\right) + \tfrac{1}{2}\left(DC - f\left(\sum W_{jk}y_j\right)^2\right) \end{aligned} \tag{15}$$

Among them, f is the activation function, net_k is the sum of the input of neurons, w_{jk} is the weight, indicating the connection strength of the j neuron to the k neuron, and y_j is the output value of the previous neuron.

We further expand the error to the input layer to obtain the following:

$$E = \frac{1}{2}\left(d - f\left[\sum W_{jk} f\left(\sum V_{ij} x_i\right)\right]^2\right) + \frac{1}{2}\left(DC - f\left[\sum W_{jk} f\left(\sum V_{ij} x_i\right)\right]^2\right) \tag{16}$$

For the output layer in the BP neural network, there are:

$$o_k = f(net_k), \quad k = 1, 2, 3, 4 \cdots, l \tag{17}$$

$$net_k = \sum_{j=0}^{m} w_{jk} y_j, \; k = 1, 2, 3, 4, \cdots, l \tag{18}$$

$$y_j = f(net_j), \quad j = 1, 2, 3, \cdots, m \tag{19}$$

$$net_j = \sum_{i=0}^{n} v_{ij} x_i, \; j = 1, 2, 3, \cdots, m \tag{20}$$

f(x) is a unipolar Sigmoid function:

$$f(x) = \frac{1}{1 + e^{-x}} \tag{21}$$

f(x) has the characteristics of continuous derivation, and has:

$$f'(x) = f(x)[1 - f(x)] \tag{22}$$

The source of error E is the difference between the actual output and the expected output, that is:

$$E = \frac{1}{2}(d - o)^2 = \frac{1}{2}\sum_{k=1}^{1}(d_k - O_k)^2 \tag{23}$$

The expressions (22) and (23) are changed to:

$$\frac{\partial E}{\partial o_k} = -(d - o) - (DC - o) = -(d + DC - 2 \cdot o) \tag{24}$$

$$\begin{aligned} \frac{\partial E}{\partial y_j} &= -(d - o) f'(net_k) W_{jk} - (DC - o) f'(net_k) W_{jk} \\ &= -(DC + d - 2 \cdot o) f'(net_k) W_{jk} \end{aligned} \tag{25}$$

when all activation functions are sigmoid:

$$f'(net_k) = f(net_k) \cdot [1 - f(net_k)] = o \cdot (1 - o) \tag{26}$$

$$f'(net_j) = f(net_j) \cdot [1 - f(net_j)] = y_j \cdot (1 - y_j) \tag{27}$$

The LSTM correlation value formula of long-term and short-term memory network is as follows:

For the value $\overset{\frown}{C}_t$: update to the value on the state, and define the formula as follows:

$$\overset{\frown}{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{28}$$

For output door O_t: determine the output value of the previous time and the input value of the current time. The definition formula is as follows:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{29}$$

The definition formula of the current time output value h_t is as follows:

$$h_t = o_t \times \tanh(C_t) \tag{30}$$

The particle swarm PSO [35] algorithm is used to optimize the LSTM model. With the increase in the number of iterations, the particles gradually gather in one or more optimal points, and the final solution is obtained. The formula is as follows:

$$v_{i,t+1} = w * v_{i,t} + c_1 * rand * (pbest_i - x_{i,t}) + c_2 * rand * (gbest_i - x_{i,t}) \tag{31}$$

$$x_{i,t+1} = x_{i,t} + \lambda * v_{i,t+1} \tag{32}$$

where $X_{i,t}$, $V_{i,t}$ represent the position and velocity of the i-th particle in the t-th iteration. $pbest_i$, gbest_i represent the individual and global optimal values, respectively. C is the learning factor, w is the weight, and λ is the speed coefficient.

If you bring Formulae (30) and (31) into Formulae (28) and (29), there are:

$$err_k^o = -\frac{\partial E}{\partial o_k} \cdot f'(net_k) = (d + DC - 2 \cdot o) \cdot o \cdot (1 - o) \cdot y_j \tag{33}$$

$$\begin{aligned} err_j^y &= -\tfrac{\partial E}{\partial y_j} \cdot f'\left(net_j\right) \\ &= \left[(d - o)f'(net_k)W_{jk} - (DC - o)f'(net_k)W_{jk}\right] \cdot y_j \cdot \left(1 - y_j\right) \\ &= \left[err_k^o \cdot W_{jk} \cdot y_j \cdot \left(1 - y_j\right)\right] \end{aligned} \tag{34}$$

Then, the Formulae (31) and (32) are substituted into the weight adjustment formula, that is, (18) and (19).

$$\Delta W_{jk} = \eta \cdot err_k^o \cdot y_j = \eta \cdot (DC - d - 2 \cdot o) \cdot o \cdot (1 - o) \tag{35}$$

$$\Delta V_{ij} = \eta \cdot err_j^y \cdot x_i = \eta \cdot [(DC - d - 2 \cdot o) \cdot o \cdot (1 - o)] \cdot W_{jk} \cdot y_j \cdot \left(1 - y_j\right) \cdot x_i \tag{36}$$

The modeling process of the decline model combined with the data-driven neural network model is as follows: First, the basic BP neural network is established, the network structure is determined, and the weights and thresholds of the neural network are initialized, and the decline curve model is constructed by calculating the decline curve [36]. The predicted value of the BP neural network and the prediction value of the decline curve model are brought into the error formula, and a new loss function is obtained. The error is backpropagated, the neural network is trained, and, when it reaches the required accuracy, the output network is simulated and predicted, and the modeling flow is shown in Figure 1.

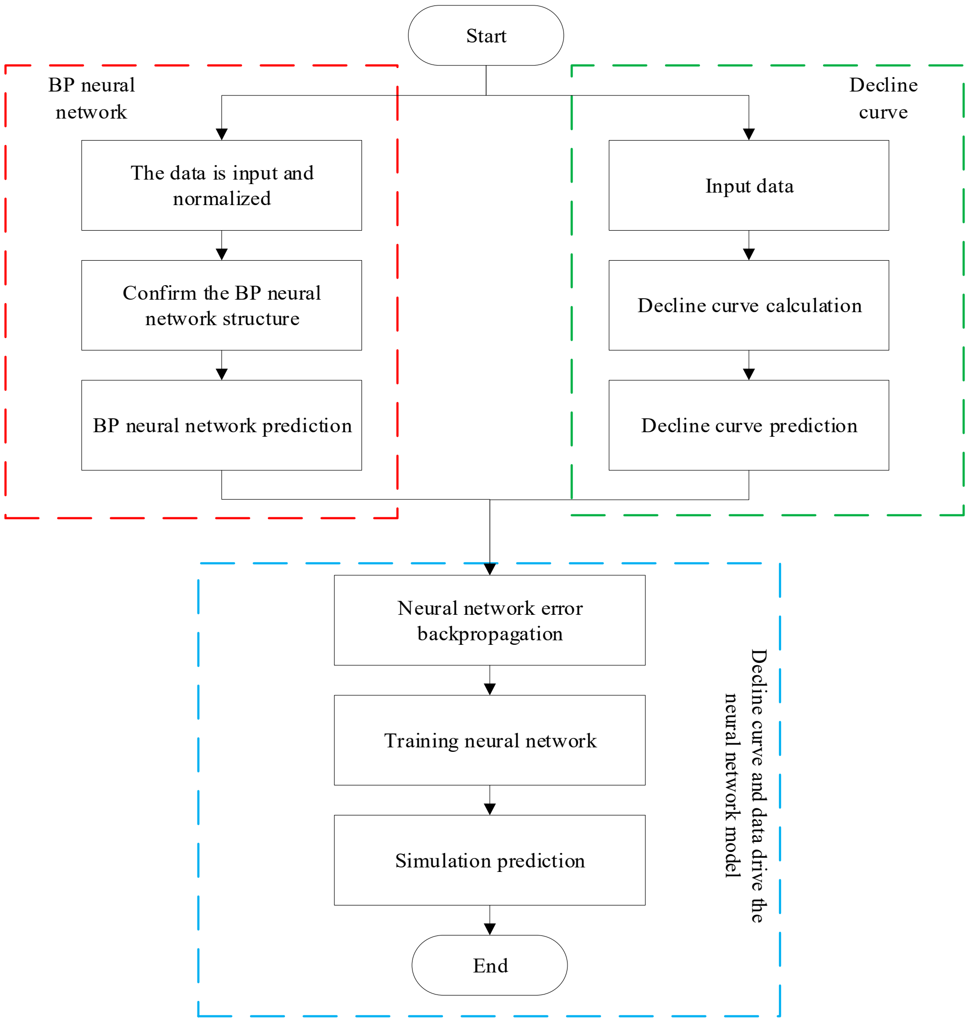

Figure 1. Flow chart of production model of tight gas well predicted by decline model combined with data-driven neural network.

4. Case Calculation and Analysis

4.1. Model Evaluation Standard

The root-mean-square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and mean square error (MSE) were selected as the evaluation indices of the model [37]. The root-mean-square error (RMSE) is used to measure the deviation between the predicted value and actual value. The smaller the root-mean-square error is, the higher the prediction accuracy is. The mean absolute error (MAE) is the average value of the absolute error between the predicted value and the actual value, which can directly reflect the actual situation of the predicted value error; the closer the value is to 0, the more accurate the prediction is. The mean absolute percentage error (MAPE) is the ratio of the absolute value of all predicted errors to the actual value; the closer the value is to 0, the more accurate the prediction is. The mean square error (MSE) refers to the average variance between the predicted value and the actual value; the closer the value is to 0, the more accurate the prediction is.

4.2. Comparative Analysis of Decline Curve Models

Based on the actual production data of fractured horizontal wells in tight gas reservoirs in the Ordos Basin, the prediction effects of three different decline curves are compared and analyzed. The prediction effects of three decline curve models and three decline curve models and data-driven models are analyzed, respectively. Among them, the initial production time to 72 months provide the actual production data of horizontal wells, and the data after 72 months are the predicted data.

It can be seen from Figure 2 that there are dramatic errors between the Arps hyperbolic model and the Arps harmonic model and the actual data, which proves that the Arps hyperbolic model and the Arps harmonic model are not suitable for the production prediction of tight gas wells. The prediction effects of the SPED model, the Arps model, and the MFF model are similar in the early stage, but, in the later stage, the prediction value of the SPED model is significantly higher than that of the other two models. The prediction effect of the Arps index model and the MFF model is similar to the actual generated data.

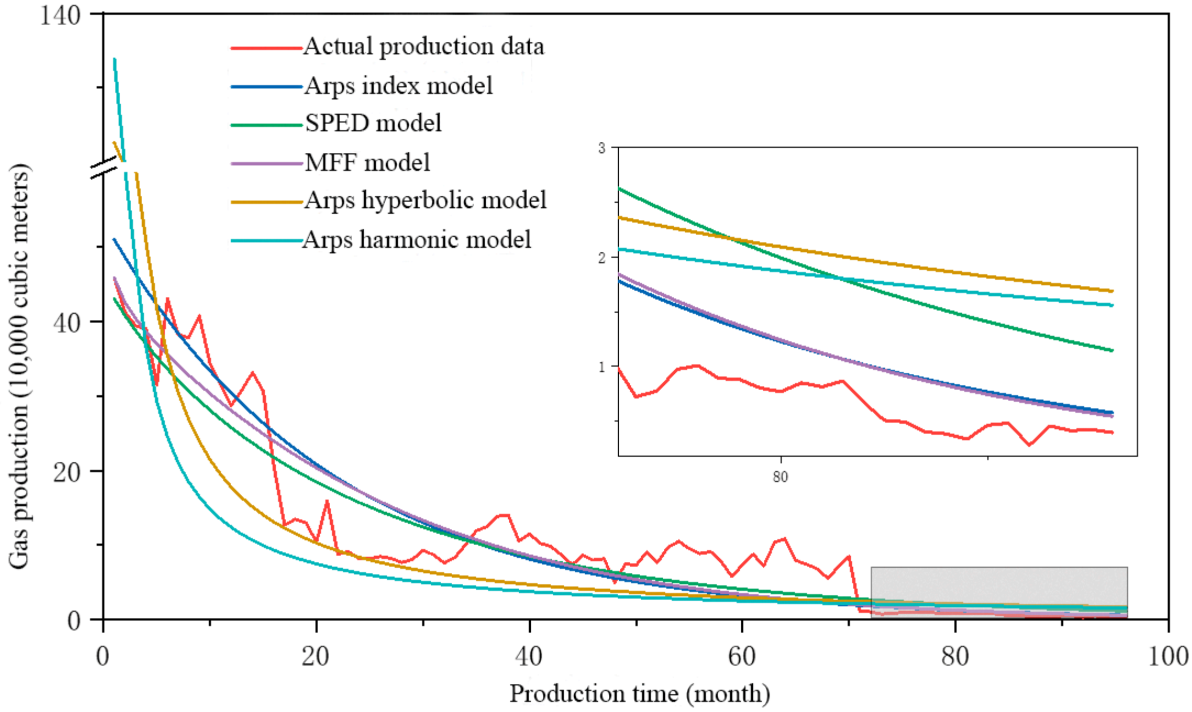

Figure 2. Prediction effect chart of different decline curves in W1 well.

In summary, through the analysis of the decline curve of the W1 well, the results show that the SPED model is not suitable for the production prediction of fractured horizontal wells in tight gas reservoirs. The prediction curves of the Arps hyperbolic model and the Arps harmonic model are obviously different from the actual data, which are also not suitable for the production prediction of fractured horizontal wells in tight gas reservoirs. The prediction effect of the Arps index model is similar to that of the MFF model, but the prediction accuracy of the MFF model is higher.

4.3. Analysis of Production Prediction of Tight Gas Wells by Decline Model Combined with Data-Driven Neural Network

In the following, the Arps model, SPED model, and MFF model are combined with a data-driven neural network, respectively, to compare and analyze the production prediction effect of tight gas wells. Among them, the initial production time to August provides the actual production data of horizontal wells, and the data after August are the model prediction data.

It can be seen from Figure 3 that there is an obvious error between the pure data-driven prediction model and the actual data, and there is an obvious error between the predicted value and the actual value when the mid-term production time is 48 months in the SPED model and the data-driven neural network model. The fitting effect of the Arps model, MFF model, and data-driven neural network model is similar within 12 months of the pre-production time. In the prediction stage, the neural network model driven by the MFF model and data is the closest to the actual data, and the prediction effect of the model is the best.

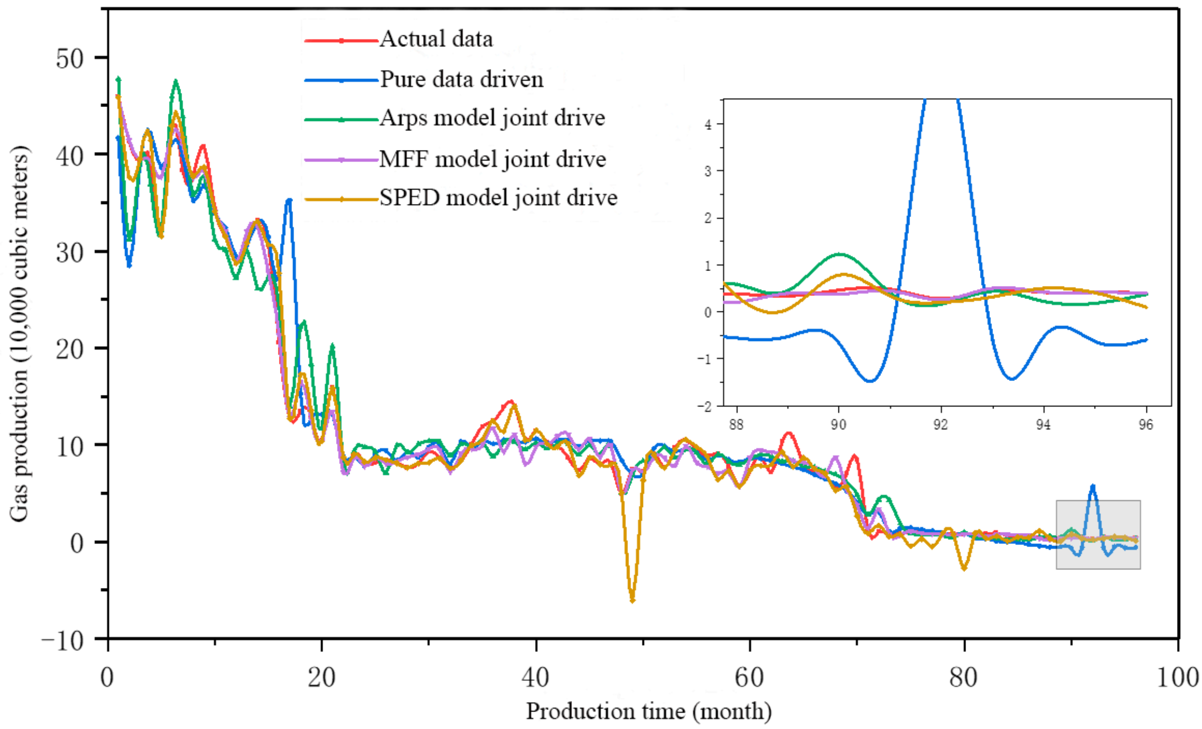

Figure 3. Comparison of production prediction by neural network model driven by different decline curves and data in well W1.

As can be seen from Table 1, the neural network model driven by the decline curve and data is obviously better than that driven by pure data. The neural network model driven by the MFF and data is better than the other two neural network models driven by the decline curve and data. The MAPE of this model is only 14.11% and the RMSE is only 1.491. The prediction results of three neural network models driven by different decline curves and data from high to low are as follows: MFF, Arps, and SPED.

Table 1. Error statistics of neural network model driven by different decline curves and data in well W1.

Evaluation Index	Pure Data Driven	Arps Model	SPED Model	MFF Model
MAPE	66.39	23.87	31.75	14.11
MAE	1.706	0.931818	1.5563	0.808
MSE	10.76	3.880	5.568	2.223
RMSE	3.280	1.969	2.359	1.491

5. Conclusions

The accurate prediction of tight gas well production plays an important role in oil and gas development. The traditional yield prediction method has strict assumptions and a low prediction accuracy in practical field application, and the generalization ability and anti-interference ability of the big data intelligent algorithm are poor. In order to solve this problem, a tight gas well production prediction method based on a decline curve and data-driven neural network is established in this paper. Through the above analysis, the following conclusions can be drawn:

1. A neural network model driven by a decline curve and data is established in this paper. In the process of data-driven model learning, the decline curve is embedded into the optimization and adjustment of the data-driven model. The original single loss func-

tion is replaced by the joint loss function of the decline curve and data-driven neural network to realize the neural network model driven by the decline curve and data. The joint data-driven model overcomes the shortcomings of the poor generalization ability and anti-jamming ability of the simple big data intelligent algorithm.

2. Using the actual production data of fractured horizontal wells in tight gas reservoirs in the Ordos Basin, the results show that the prediction effect of the SPED model is not good and is not suitable for the prediction of fractured horizontal wells in tight gas reservoirs. The prediction curves of the Arps hyperbolic model and Arps harmonic model are obviously different from the actual data, which are also not suitable for the prediction of fractured horizontal wells in tight gas reservoirs. The prediction effect of the Arps index model is similar to that of the MFF model, but the prediction curve of the MFF model is closer to the actual curve and the effect is better.
3. Through the actual production data of fractured horizontal wells in tight gas reservoirs in the Ordos Basin, the production prediction effect of the neural network model driven by different decline curves and data is analyzed. The accuracy of the MFF model and data-driven model is the highest. The average absolute percentage error of model prediction is 14.11%, the average absolute error is 0.808, the root-mean-square error is 1.491, and the mean square error is 2.223. The prediction results of three neural network models driven by different decline curves and data are ranked from high to low as follows: the neural network model driven by MFF and data, the neural network model driven by Arps and data, and the neural network model driven by SPED and data.
4. Tight gas production is an important part of the global energy industry and is essential to the energy supply and economic development of modern societies. However, over time, traditional tight gas drilling has faced many challenges and constraints, and, in order to meet these challenges, the petroleum industry needs to continue to innovate and improve, drive technological advances, and improve extraction efficiency and environmental protection. The accurate prediction of gas well production is one of the key factors affecting the economical and efficient development of tight gas wells. In this paper, the principles of different decline curves are introduced, and the construction principle of the combined data-driven model of decline curves is briefly described. A combined data-driven model of decline curves was constructed. Several decline curves were compared and analyzed by the actual production data of fractured horizontal wells in tight gas reservoirs, and the MFF curve was the best. Then, the prediction effect of different decline curves and the combined data-driven models is compared and analyzed, and the accuracy of the MFF model and combined data-driven model is the highest. This method effectively avoids the problem of the strict assumptions of traditional production forecasting methods, and improves the prediction accuracy in actual field application. At the same time, it also avoids the problem of the poor generalization ability and anti-interference ability of the big data intelligent algorithm.

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References

1. Valko, P.P.; Lee, W.J. A Better Way to Forecast Production from Unconventional Gas Wells. In Proceedings of the SPE Annual Technical Conference and Exhibition, Florence, Italy, 20–22 September 2010.
2. Yuan, H.; Soar, L.; Xu, J. A Case Study to Evaluate Shale Oil Production Performance Models with Actual Well Production Data. In Proceedings of the SPE Unconventional Resources Technology Conference, Denver, CO, USA, 12–14 August 2013; Paper SPE 1582234.
3. Duong, A.N. Rate-decline analysis for fracture-dominated shale reservoirs. *SPE Reserv. Eval. Eng.* **2011**, *14*, 377. [CrossRef]
4. Lee, J.; Sidle, R. Gas reserves estimation in resource plays. *SPE Econ. Manag.* **2010**, *2*, 86–91. [CrossRef]
5. Kabir, S.; Rasdi, F.; Igboalisi, B. Analyzing production data from tight oil wells. *J. Can. Pet. Technol.* **2011**, *50*, 48–58. [CrossRef]
6. Fetkovich, M.J. Decline Curve Analysis Using Type Curves. *J. Pet. Technol.* **1980**, *32*, 1065–1077. [CrossRef]
7. Agarwal, R.G.; Gardner, D.C.; Kleinsteiber, S.W.; Fussell, D.D. Analyzing Well Production Data Using CombinedType-Curve and Decline-Curve Analysis Concepts. *SPE Reserv. Eval. Eng.* **1999**, *2*, 478–486. [CrossRef]
8. Blasingame, T.A.; Mccray, T.L.; Lee, W.J. *Decline Curve Analysis for Variable Pressure Drop/Variable Flowrate Systems*; Society of Petroleum Engineers: Richardson, TX, USA, 1991.
9. Warren, J.E.; Root, P.J. The Behavior of Naturally Fractured Reservoirs. *Soc. Pet. Eng. J.* **1963**, *3*, 245–255. [CrossRef]
10. Sun, R.; Zhang, Y.; Zhang, X.; Hu, J.; Li, Z. Productivity prediction model and parameter analysis of fracturing horizontal well in dual medium tight reservoir. *Sci. Technol. Eng.* **2019**, *19*, 89–96.
11. Xiao, Z.; Zhao, Y.; Zhang, L.; Ge, F.; Yang, Z.; Liu, X.; Zhang, D.; Tian, Y. Influencing factors of tight reservoir productivity based on dual-medium embedded discrete fracture model. *Sci. Technol. Eng.* **2023**, *23*, 10780–10790.
12. Luo, E.; Hu, Y.; Wang, L.; Cao, C. Analysis method of production decline of horizontal wells with dual media. *Mod. Geol.* **2013**, *27*, 1440–1444.
13. Larsen, L.; Hegre, T.M. Pressure transient analysis of multifractured horizontal wells. In Proceedings of the SPE Annual Technical Conference and Exhibition, New Orleans, LA, USA, 21–4 August 1994; Society of Petroleum Engineers: Richardson, TX, USA, 1994.
14. Raghavan, R.S.; Chen, C.C.; Agarwal, B. An analysis of horizontal wells intercepted by multiple fractures. *SPE J.* **1997**, *2*, 235–245. [CrossRef]
15. Ozkan, E.; Brown, M.L.; Raghavan, R.S.; Kazemi, H. Comparison of fractured horizontal-well performance in conventional and unconventional reservoirs. In Proceedings of the SPE Western Regional Meeting, San Jose, CA, USA, 4–7 March 2009; Society of Petroleum Engineers: Richardson, TX, USA, 2009.
16. Yao, J.; Liu, P.; Wu, M. Well test analysis of fractured horizontal well in fractured reservoir. *J. China Univ. Pet.* **2013**, *37*, 107–113.
17. Su, Y.; Wang, W.; Zhou, S.; Li, X.; Mu, L.; Lu, M.; Sheng, G. Volume three linear flow model of fractured horizontal well and fracture arrangement of volumetric fractured horizontal wells. *Oil Gas Geol.* **2014**, *35*, 435–440.
18. Ren, Z.; Wang, X.; Cui, S.; Yang, X.; Yang, Q.; Bi, G. Semi-analytical percolation model of volume fracturing horizontal well in tight reservoir. *Fault Block Oil Gas Fields* **2018**, *25*, 488–492.
19. Liao, R.; Wu, Z.; Xu, Y.; Mu, L. The amount of sand used for fracturing is optimized by artificial neural network technology. *J. Pet. Nat. Gas (J. Jianghan Inst. Pet.)* **2005**, *214*, 134.
20. Ni, H.; Liu, Y.; Fan, Y.; Li, P. Optimization of steam drive injection and production scheme based on improved particle swarm optimization. *Acta Pet. Sin.* **2014**, *35*, 114–117.
21. Klie, H. Physics-based and data-driven surrogates for production forecasting. In Proceedings of the Reservoir Simulation Symposium, Houston, TX, USA, 23–25 February 2015. SPE 173206.
22. Raphael, S.; Fuge, C.P.; Gutierrez, S.; Kuzma, H.A.; Arora, N.S. Big Data Every Day: Predictive Analytics Used to Improve Production SurveilIance. In Proceedings of the Digital Energy Conference and Exhibition, The Woodlands, TX, USA, 3–4 March 2015; SPE 173444.
23. Cao, Q.; Banerjee, R.; Gupta, S.; Li, J.; Zhou, W.; Jeyachandra, B. Data Driven Production Forecasting Using Machine Leaming. In Proceedings of the Argentina Exploration and Production of Unconventional Resources Symposium, Buenos Aires, Argentina, 1–3 June 2016. SPE 180984.
24. Jia, X.; Zhang, F. Applying Data-Driven Method to Production Decline Analysis and Forecasting. In Proceedings of the SPE Annual Technical Conference and Exhibition, Dubai, United Arab Emirates, 26–28 September 2016; Society of Petroleum Engineers: Richardson, TX, USA, 2016. SPE 181616.
25. Liu, W.; Liu, W.; Gu, J. Prediction of daily oil production of oil wells based on machine learning method. *Pet. Drill. Prod. Technol.* **2020**, *542*, 70–75. [CrossRef]
26. Gu, J.; Zhou, X.; Wang, S. Oil field production prediction method based on Lasso algorithm. *Sci. Technol. Eng.* **2020**, *20*, 10759–10763.
27. Ma, X.; Fan, Y. Productivity prediction model of fracturing vertical well based on machine learning. *Pract. Underst. Math.* **2021**, *51*, 186–196.

28. Han, S.; Che, M.; Su, W.; Xiao, Y.; Wu, Z.; Chen, J.; Wang, L. Single well production prediction method and application of shale gas in Weiyuan block of Sichuan basin. *Spec. Oil Gas Reserv.* **2022**, *29*, 141–149.
29. Cheng, B.; Xu, T.; Luo, S.; Chen, T.; Li, Y.; Tang, J. Prediction method and practice of favorable reservoir of deep shale based on machine learning. *Pet. Explor. Dev.* **2022**, *449*, 918–928. [CrossRef]
30. Li, J.; Qin, S.; Wang, J.; Liang, C.; Chen, Y.; Hu, K. Application of random forest algorithm in Jimusar shale reservoir. *J. Chang. Univ. (Nat. Sci. Ed.)* **2023**, *323*, 1–8. [CrossRef]
31. Park, J.; Datta-Gupta, A.; Singh, A.; Sankaran, S. Hybrid physics and data-driven modeling for unconventional field development and its application to US onshore basin. *J. Pet. Sci. Eng.* **2021**, *206*, 109008. [CrossRef]
32. Xue, L.; Dai, C.; Han, J.; Yang, M.; Liu, Y. Depth neural network model driven by reservoir percolation physics and data. *Oil Gas Geol. Oil Recovery* **2022**, *29*, 145–151. [CrossRef]
33. Li, X.; Ma, X.; Xiao, F.; Xiao, C.; Wang, F.; Zhang, S. A physics-constrained long-term production prediction method for multiple fractured wells using deep learning. *J. Pet. Sci. Eng.* **2022**, *217*, 110844. [CrossRef]
34. Wang, H.; Wang, M.; Chen, S.; Hui, G.; Pang, Y. A Novel Governing Equation for Shale Gas Production Prediction via Physics-informed Neural Networks. *Expert Syst. Appl.* **2024**, *248*, 123387. [CrossRef]
35. Arps, J.J. Analysis of Decline Curves. *Trans. AME* **1945**, *160*, 228–247. [CrossRef]
36. Valko, P.P. Assigning value to stimulation in the Barnett shale: A simultaneous analysis of 7000 plus production histories and well completion records. In Proceedings of the SPE Hydraulic Fracturing Technology Conference and Exhibition, The Woodlands, TX, USA, 19–21 January 2009. SPE 119369.
37. Huang, Z.; Pan, Y.; Cao, X. Research on the basic theory and improvement of particle swarm optimization. *Silicon Val.* **2014**, *7*, 36.