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Market prediction of self-sold products in oilfield based on optimized GM (1, 1) model

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Abstract

It is a key link in the expansion of natural gas business to sell independent products in oil and gas high and medium-sized oilfields to transform the advantages of oilfield resources into benefits How to effectively predict the demand of oil and gas products market is very important to improve the oilfield management mechanism and marketing ability In view of the fuzzy market of self-sold products at present, grey prediction can be used from the perspective of data refinement Because the classical GM (1, 1) model is not enough in forecasting accuracy, this paper optimizes the background value and initial conditions that affect the forecasting effect of the model to improve the accuracy of GM (1, 1) model, and establishes a forecasting model for market demand of self-sold products Based on the statistical data of oilfield market demand in recent years, the market demand in the future from 2023 to 2026 is predicted The forecast results show that the market demand is on the rise, and the market demand of self-sold products will have a strong growth state in the future The model achieves the expected goal on the actual market demand data, and has the advantages of simple modeling and strong self-adaptability in application, which provides certain reference value for oilfield to implement independent product sales plan.

Keywords: *market demand, Sell products independently, GM (1, 1) model, Background value, Initial condition.*

1. INTRODUCTION

Today, with the continuous and in-depth implementation of the new national energy security green and low-carbon strategy, promoting the natural gas business to accelerate the transformation of resource advantages into benefit advantages and carrying out market-oriented reform is an important content of oilfield "oil" reform With the oil field vigorously promoting the original exploration technology with important influence in China, the output of scattered natural gas and light hydrocarbons is gradually becoming more intelligent and mature, and the original single customer direct sales can no longer meet the market-oriented operation mechanism, and it is necessary to build a new diversified modern market pattern. At present, the self-sold products lack competition and are not suitable for the market-oriented operation of "oil". It is necessary to grasp the marketing policy of "market-oriented, customer-oriented, sales-fixed production, production promotion, integration, cooperation, competition and win-win" more accurately, and improve the production and operation efficiency. The oilfield should effectively promote the improvement of the operating mechanism and enhance the marketing ability of oil and gas products to inject strong power into the promotion of high The market uncertainty of self-selling products is more, accurately grasping the market vacancy and improving the economic benefit is the focus of oilfield attention. Based on the present situation of self-selling products in oilfield, studying the market demand of self-selling products in oilfield can have certain reference value for oilfield to plan self-selling products, realize economic benefit, promote oilfield market reform, and realize high benefit.

It is very necessary for scholars at home and abroad to pay close attention to the study of market demand for selling products and correctly estimate the market demand If the estimated demand decreases, the business will be lost, but if the estimated demand is high, the working capital will be prevented until the market sells excess production At present, the research models for market demand forecasting include time series model, regression model, neural network model and grey forecasting model However, the market situation of self-selling products is more complex, and the clear influencing factors are mostly qualitative factors, which are difficult to judge quantitatively. GM (1, 1) model, as a classical grey prediction model, can transform the complex influencing factors into grey system, and use the form of

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equation to concretize and apply widely put forward a new seasonal grey model with dynamic seasonal factors through Matlab programming (Wang Z et al., 2020). The results can effectively identify the dynamic changes of seasonal factors and significantly improve the prediction accuracy forecasts the energy demand by GM (1, 1) model (Hu Y C, 2020), and predicts the specific energy demand for a period of time in the future used the grey model GM (1, 1) to construct different levels of birth defect incidence prediction models and evaluate the prediction models (Peng Z R et al., 2022). Based on the basic principle of weakening buffer operator and linear transformation, GM (1, 1) model is improved. The accuracy of GM (1, 1) model is compared with that of GM (1, 1) model by means of mean square error ratio small probability error and average relative error used the improved GM (1, 1) model to predict the population of Xinjiang (Hou R H et al., 2021). The results show that compared with the classical GM (1, 1) model, the improved model is more accurate and more stable in population prediction(Zhang A L et al., 2020), which is more suitable for medium population prediction constructed GM (1, 1) model to predict the fluctuation of real estate price based on the average annual house price data of Baotou City from 2015 to 2019, and then made short-term statistical prediction on the change trend of real estate price in Baotou City in the next three years. The price simulated by this model has a high degree of fitting with the real price, and the prediction effect of the model is good also verified the reliability of grey model GM (1, 1) in pine growth prediction (Jiao Y Q et al., 2020). This mathematical model has a good application prospect in tree stochastic growth prediction. Bao Xu et al. optimized GM (1, 1) model, which can significantly improve the prediction accuracy (Bao X et al., 2020).

This paper selects the market demand data of self-selling products in recent years as the initial value, makes full use of the basic data, and makes comprehensive optimization based on background value and initial conditions when using GM (1, 1) model to enhance the anti-random interference ability of the model (Zheng X P et al., 2021). Finally, it accurately predicts the market demand of self-selling products in the next few years by using the model.

2. Establishment of improved GM (1, 1) model

2.1 Construction of basic GM (1, 1) model

Determine the original sequence according to the demand situation of the oil field self-sold product market in recent years;

$$X^{(0)} = \{X^{(0)}(1), X^{(0)}(2), \cdots, X^{(0)}(n)\} \quad (1)$$

$X^{(0)}(i)$ indicates that the annual market demand is non-negative;

Then, a new sequence is generated by accumulating on the basis of the original sequence: $X^{(1)} = \{X^{(1)}(1), X^{(1)}(2), \cdots, X^{(1)}(n)\}$

Where $X^{(1)}(i) = \{\sum_{j=1}^{i} x^{(0)}(j) | i = 1,2 \cdots, n\}$, the main purpose of generating accumulation sequence is to transform unordered data into ordered data and make it more stable The first-order whitening differential equation is generated by modeling the new sequence:

$$\frac{dX^{(1)}}{dt} + aX^{(1)} = b$$

Where a and b are undetermined coefficients a is grey number b is endogenous control grey number.

On this basis, the grey differential equation corresponding to the whitening differential equation is generated in order to introduce the optimization of background value The grey differential equation is:

$$X^{(0)}(k) + aZ^{(1)}(k) = b$$

The $Z^{(1)}(k)(k = 1,2,3 \dots n)$ is the optimizable background value calculation formula is:

$$Z^{(1)}(k) = \frac{1}{2}(X^{(1)}(k-1) + X^{(1)}(k))$$

Let $A = [a \quad b]^T$, if A is estimated by least square method, then there is $A = (B^T B)^{-1} B^T Y$.

Among them,

$$B = \begin{bmatrix} -\frac{[X^{(1)}{}_{(1)} + X^{(2)}{}_{(2)}]}{2} & 1 \\ \dots\dots & 1 \\ -\frac{[X^{(1)}{}_{(m-1)} + X^{(2)}{}_{(m)}]}{2} & 1 \end{bmatrix} = \begin{bmatrix} -Z^{(1)}(2) & 1 \\ \dots\dots & 1 \\ -Z^{(1)}(m) & 1 \end{bmatrix}$$

$$Y = X^{(0)}(2), X^{(0)}(3), \cdots, X^{(0)}(n)^T$$

The grey prediction time response function is obtained by solving the dynamic model of the original first-order differential equation: $\hat{X}^{(1)}(k+1) = \left[X^{(0)}(1) - \frac{b}{a}\right] e^{-ak} + \frac{b}{a}$ $(k = 0,1,2, \dots n)$

The predicted value is reduced to: $\hat{X}^{(0)}(k+1) = \left[\hat{X}^{(1)}(k+1) - \hat{X}^{(1)}(k)\right] = (1 - e^{a}) \left[X^{(0)}(1) - \frac{b}{a}\right] e^{-ak}$, $k = 1,2 \dots n$

2.2 GM (1, 1) model optimization

The purpose of integrating the original dynamic model of first-order differential equation $\frac{dX^{(1)}}{dt} + aX^{(1)} = b$ in interval range is to transform the background value into the interval $[k-1, k]$($k = 2, 3 \dots n$) by integrating $\frac{dX^{(1)}}{dt} + aX^{(1)} = b$: $\int_{k-1}^{k} \frac{dX^{(1)}}{dt} dt + \int_{k-1}^{k} aX^{(1)} dt = \int_{k-1}^{k} b \, dt$

There is $X^{(1)}(k) - X^{(1)}(k-1) + \int_{k-1}^{k} aX^{(1)} dt = b$. From the basic principle of accumulation sequence, we can see that $X^{(1)}(k) - X^{(1)}(k-1) = X^{(0)}(k)$ integration result is: $X^{(0)}(k) + \int_{k-1}^{k} aX^{(1)} dt = b$

Comparing with the grey differential equation $X^{(0)}(k) + aZ^{(1)}(k) = b$, we can see that $Z^{(1)}(k) = \int_{k-1}^{k} X^{(1)} dt$。And $X^{(1)}(k)$ is an increasing function. According to the mean value theorem of integral, $X^{(1)}(k-1) < \int_{k-1}^{k} X^{(1)} dt < X^{(1)}(k)$。If $\alpha (0 < \alpha < 1)$ is introduced, then there is a value of $\int_{k-1}^{k} X^{(1)} dt = \alpha X^{(1)}(k-1) + (\alpha) X^{(1)}(k)$.

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The estimated value of the undetermined coefficient a'，b'，α obtained by optimization based on the background value is (Xu N et al., 2015):$\begin{cases} a' = \ln(a+1) \\ b' = \frac{b*\ln(a+1)}{a} \\ \alpha = \frac{1}{\ln(a+1)} - \frac{1}{a} \end{cases}$

Where a，b is $A = [a \quad b]^T$ in GM (1, 1) model is obtained by least square method.

In the initial condition, the original GM (1, 1) model generates the accumulation sequence by taking the first data in the original sequence as the initial condition, but this condition is not the latest information of the accumulation sequence, so now we want to update it by optimization to realize "new information first" (Xiong P P et al., 2015).The original $\hat{X}^{(1)}(1) = X^{(0)}(1)$ is modified and converted to $\hat{X}^{(1)}(1) = X^{(0)}(1) + c$, where c is the correction factor, and the function of the original model can be written as:$\hat{X}^{(0)}(k+1) = \left[\hat{X}^{(1)}(k+1) - \hat{X}^{(1)}(k)\right] = (1 - e^{a'})\left[X^{(0)}(1) - \frac{b'}{a'} + c\right] e^{-a'k}$

Considering that there are multiple criteria for the correction term, the minimum criteria and mean square error are used to calculate the boundary value correction term from the original sequence and the new sequence generated by accumulation (Zhang B et al., 2013).

The error of the new predicted value of the original sequence is the smallest in the sense of least squares, and the correction coefficient is as follows:

$$\min_{c} \sum_{k=1}^{n} [\tilde{X}^{(1)}(k) - X^{(0)}(1)]$$

$$c = \frac{\gamma}{\delta} - [X^{(0)}(1) - \frac{b'}{a'}]$$

Where $\gamma = \sum_{k=1}^{n} X^{(0)}(k)\, e^{-a'k}$；$\delta = (1 - e^{a'})\frac{1-e^{-2na'}}{1-e^{-2a'}}$.

The error of the new predicted value of the accumulated generated sequence is the smallest in the sense of least squares, and the correction coefficient is as follows:$c = \{\varepsilon - \theta\left[X^{(0)}(1) - \frac{b'}{a'}\right] - \frac{b'}{a'}\mu\}/\theta$

Where $\varepsilon = \sum_{k=1}^{n} X^{(1)}(k)\, e^{-a'k}$；$\theta = \frac{1-e^{-2na'}}{1-e^{-2a'}}$；$\mu = \frac{1-e^{-na'}}{1-e^{-a'}}$. In practical application, we can calculate the results according to two criteria respectively, and then choose the better one. In this paper, we consider the use of data and the selection of correction coefficient c, and use the prediction of cumulative generation sequence to estimate.

2.3 Optimized GM (1, 1) model prediction steps

The basic flow of GM (1, 1) model for comprehensive optimization is as follows.

Step 1: Original Sequence $X^{(0)}$

Step 2: A new sequence $X^{(1)}$ is generated by superimposing the original sequence once

Step 3: Using model formula to find grey number a and endogenous control grey number b

(Background Value Optimization)

Step 4: Generate a new grey number a' and endogenously control the grey number b'
(Initial Condition Optimization)

Step 5: Generate correction factor c

Step 6: Bring in the new function model evaluation

2.4 Model Accuracy Test

The GM (1, 1) model accuracy test should first be carried out according to the grey number a value to predict the feasibility of the data and the applicable scenario (prediction time span), and then through the residual error test to judge the accuracy of the model accuracy synthetically According to the value of grey number a, the feasibility of forecasting data and the specific applicable scope of applicable scenarios are shown in Table 1.

Table 1 Scope of application of GM (1, 1) model

Grey number	Applicable scope of GM (1, 1) model
$\lvert a \rvert \geq 2$	The model is meaningless
$-a \leq 0.3$	Can be used for medium prediction
$0.3 < -a \leq 0.5$	Prediction should be used with caution in short-term prediction
$0.5 < -a \leq 0.8$	Short-term forecasting is very cautious
$0.8 < -a \leq 1$	GM (1, 1) model should be modified by residual value
$-a > 1$	GM (1, 1) model is not suitable for prediction

The correlation of residual test mainly wants to judge the validity of the model. The basic formula of the relative error is $\varphi(k) = \frac{\Delta(k)}{x^{(0)}(k)} \times 100\%$ where $\Delta(k) = X^{(0)}(1) - \hat{X}^{(0)}(k) \quad (k = 1,2 \ldots\ldots n)$. The error between the predicted value and the true value of the model is used as the main data. On this basis, the average relative error is $\varphi_k = \frac{1}{n-1}\sum_{k=2}^{n}\left|\frac{\Delta(k)}{x^{(0)}(k)}\right|$.

After residual test, the specific steps for calculating mean square error ratio Z and small error probability P are as follows:

(1) Calculate the mean and mean square error of the original sequence:$S_1 = \sqrt{\frac{\sum_{k=1}^{n}[X^{(0)}(k) - X^{(0)}]^2}{n}}$

(2) Calculate the mean error and mean square error of the absolute error sequence (0) :$S_2 = \sqrt{\frac{\sum_{k-1}^{n}\left[\Delta(k) - \bar{\Delta}\right]^2}{n}}$

(3) Calculate the mean square error ratio:$Z = \frac{S_2}{S_1}$

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(4) Calculate the probability of small error: $P = P(\left|\Delta^{(0)}(i) - \bar{\Delta}^{(0)}\right| < 0.6745S_1) k = 1,2,\cdots,n$

By calculating the average relative error φ_k mean square error ratio Z, small error probability P, the residual test is carried out to judge whether the model is reasonable or not. According to the obtained value, refer to Table 2 to judge the accuracy of the model.

Table 2 Reference table of GM (1, 1) model accuracy inspection grade

Model accuracy grade	Average relative error （φ_k）	Mean square error ratio Z	Small error probability P
Level 1 (excellent)	$\varphi_k \le 0.01$	$Z \le 0.35$	$P \ge 0.95$
Level 2 (good)	$0.01 < \varphi_k \le 0.05$	$0.35 < Z \le 0.50$	$0.80 \le P < 0.95$
Level 3 (qualified)	$0.05 < \varphi_k \le 0.10$	$0.50 < Z \le 0.65$	$0.70 \le P < 0.80$
Level 4 (barely)	$0.10 < \varphi_k \le 0.20$	$0.65 < Z \le 0.80$	$0.60 \le P < 0.70$
Unqualified	$\varphi_k > 0.20$	$Z > 0.80$	$P < 0.60$

3. Examples

Products independently sold by oilfield include scattered gas, light hydrocarbon, and condensate oil According to classification statistics, including city gas, chemical fertilizer, LNG plant, CNG, petroleum refining, glass ceramic metallurgy, power generation, and distributed energy, etc. Through investigation, the energy demand around the oil field sales in a certain area of China is shown in Table 3 below.

Table 3 Demand of oil and gas by-products from 2018 to 2022

Year	2018	2019	2020	2021	2022
Scattered gas demand	22.84	24.13	24.88	25.7	27.65
Light hydrocarbon demand	33.55	35.7	37.44	37.19	42.55
Condensate oil demand	59.46	60.73	62.48	64.19	67.53

According to the basic flow of GM (1, 1) model, the original sequence is as follows: $\begin{cases} X_S^{(0)} = \{22.84,\ 24.13,\ 24.88,\ 25.7,\ 27.65\} \\ X_L^{(0)} = \{33.55,\ 35.7,\ 37.44,\ 37.19,\ 42.55\} \\ X_C^{(0)} = \{59.46,\ 60.73,\ 62.48,\ 64.19,\ 67.53\} \end{cases}$

Then, a new sequence is generated by accumulating on the basis of the original sequence:

$$\begin{cases} X_S^{(1)} = \{22.84,\ 46.97,\ 71.85,\ 97.55,\ 125.2\} \\ X_L^{(1)} = \{33.55,\ 69.25,\ 106.69,\ 143.88,\ 186.43\} \\ X_C^{(0)} = \{59.46,\ 120.19,\ 182.67,\ 246.86,\ 314.39\} \end{cases}$$

According to the whitening differential equation $\frac{dX^{(1)}}{dt} + aX^{(1)} = b$, the endogenous control grey number b of grey number a is obtained by least square method.

$$\begin{cases} a_S = -0.0449 \\ b_S = 22.3323 \end{cases};\ \begin{cases} a_L = -0.0541 \\ b_L = 32.4055 \end{cases};\ \begin{cases} a_C = -0.0349 \\ b_C = 57.3131 \end{cases}$$

Optimization formula based on background value and original condition, $\begin{cases} a' = \ln(a+1) \\ b' = \frac{b*\ln(a+1)}{a} \\ \alpha = \frac{1}{\ln(a+1)} - \frac{1}{a} \end{cases}$

And $c = \{\varepsilon - \theta\left[X^{(0)}(1) - \frac{b'}{a'}\right] - \frac{b'}{a'}\mu\}/\theta$ can be obtained:

$$\begin{cases} a'_S = -0.0459 \\ b'_S = 22.8492 \\ c = 11.2920 \end{cases};\ \begin{cases} a'_L = -0.0556 \\ b'_L = 33.3150 \\ c = 17.1757 \end{cases};\ \begin{cases} a'_C = -0.0355 \\ b'_C = 58.3371 \\ c = 34.4912 \end{cases}$$

According to the original data, the optimized grey GM (1, 1) forecasting model is used to forecast the market demand of self-sold products in oilfield and test the accuracy. The test results show that the prediction model of oil and gas by-products with $-a$ less than 0.3 is effective and suitable for the forecast scenario; In the post-residual test, the mean square error ratio is small, and the calculation results of error probability are all of the first-order prediction accuracy is higher. Compared with GM (1, 1) model, the GM (1, 1) model optimized by GM (1, 1) model is used to forecast the demand quantity according to the original data. The forecast results of the two different models are shown in Table 4.

Table 4 Comparison of model prediction results

Year	**GM (1, 1) model of**		**Optimized GM (1, 1) model**	
	Forecast result	**Relative error**	**Forecast result**	**Relative error**

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Scattered gas (unit: 100 million cubic meters)				
2017	22.84	0	22.84	0
2018	23.88	0.009	24.09	0.002
2019	24.98	0.004	25.01	0.005
2020	26.13	0.017	25.81	0.004
2021	27.33	0.011	27.55	0.003
Light hydrocarbons (unit: 10,000 tons)				
2017	33.55	0	33.55	0
2018	35.16	0.015	35.46	0.006
2019	37.12	0.008	37.5	0.002
2020	39.18	0.053	38.16	0.030
2021	41.36	0.028	42.65	0.002
Condensate oil (unit: 10,000 tons)				
2017	59.46	0	59.46	0
2018	60.43	0.005	60.86	0.002
2019	62.57	0.002	62.31	0.003
2020	64.79	0.009	64.7	0.008
2021	67.09	0.006	67.23	0.004

Table 4 shows that the optimized GM (1, 1) model has higher prediction accuracy and smaller average relative error; The prediction accuracy of the improved model is significantly higher than that of GM (1, 1) model, and the prediction results are obviously affected by data fluctuations. The stability of this model is poor when it is used in medium prediction, but the prediction accuracy is improved when it is optimized by background value and original conditions, and the prediction results are relatively stable and suitable for medium prediction. Therefore, the optimized GM (1, 1) model is used to predict the market demand of self-sold products from 2023 to 2026, which is shown in Table 5.

Table 5 Forecast results of market demand for self-sold products

Year	2023	2024	2025	2026
Scattered gas	28.07	29.2	30.49	31.67
Light hydrocarbon	43.61	45.36	65.32	68.05
Condensate oil	69.37	72.36	75.46	78.52

4. Conclusion

(1) For oilfields, understanding the market demand of self-sold products is a key link to realize high efficiency by sales-fixed production-production promotion In this paper, an improved GM (1, 1) model is established for the complexity of market information of self-selling products. The model can forecast the market demand of self-selling products by optimizing the background value and initial conditions.

(2) The optimized GM (1, 1) model inherits the advantages of GM (1, 1) model and optimizes the background value, and corrects the information effectively to ensure that the average relative error of optimized GM (1, 1) model is smaller than that of GM (1, 1) model.

(3) As a new business scope of oilfield, the market of self-selling products is complex and unfamiliar. This paper uses the optimized GM (1, 1) model to achieve smaller prediction error, which is an effective attempt for oilfield to predict the product market and provides a feasible prediction for the medium prediction of product demand quantity. It has practical value.

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