MACHINE LEARNING-BASED EVALUATION OF ACIDIZING EFFECTIVENESS AND OPTIMIZATION OF ACIDIZING PARAMETERS FOR CARBONATE GAS RESERVOIR HORIZONTAL WELLS

by

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The Dengsi formation in the Gaoshiti-Moxi block of the Sichuan Basin is characterized as having low porosity and low permeability. Typically, the development is carried out using horizontal wells and segmented acid fracturing techniques. In this study, based on a data-driven approach, geological, engineering, and well testing data were collected from 22 horizontal wells in the study area. Then, a high precision acid fracturing productivity model was established using Gaussian process regression. This model exhibited a high level of prediction accuracy, with an average relative error of only 8.77% for the test dataset. Furthermore, leveraging the established productivity model and employing a particle swarm optimization algorithm, research was conducted to optimize acid fracturing parameters and predict well productivity. The practical application of this approach in one well yielded favorable results, which hold promise for providing guidance on segmented acid fracturing design in the study area.

Key words: *carbonate gas reservoirs, horizontal wells, acidizing, productivity evaluation, data-driven*

Introduction

The Upper Permian Dengying Formation, Deng 4th Member carbonate gas reservoir in the Gaoshiti-Moxi area of the Sichuan Basin is characterized by deep burial and high temperatures. Additionally, the average reservoir porosity is 3.22%, and permeability ranges from 0.01-10 mD, making it a low porosity, low permeability reservoir [1]. Development mainly relies on horizontal wells and segmented acidizing techniques [2]. The Deng 4th Member carbonate gas reservoir exhibits strong heterogeneity, resulting in significant variations in well productivity [3]. Targeted acidizing modifications are required to effectively utilize the reserves and enhance single-well development performance [4, 5]. Acidizing effectiveness is primarily influenced by geological and engineering parameters, including reservoir permeability, porosity, water saturation, acid volume, and injection rate.

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Common acidizing effectiveness prediction methods include analytical models and numerical simulations [6]. However, analytical models require artificial assumptions such as constant temperature and Newtonian fluids, which may deviate significantly from actual conditions [7, 8]. Numerical simulation methods demand high accuracy in input data, as errors in the data can lead to substantial calculation inaccuracies. Furthermore, there is no mature method for accurately identifying and characterizing underground fracture networks. Consequently, accurately predicting acidizing effectiveness is highly challenging.

Currently, data-driven methods without the need for physical modelling have sparked revolutionary changes in various fields such as finance, medicine, and security. Therefore, this study, based on a data-driven approach, utilizes machine learning algorithms in combination with geological, engineering, and well testing data from previous acidizing wells to conduct productivity evaluations for acidizing wells. It also investigates the impact of geological and engineering parameters on the acidizing effectiveness of individual wells, aiming to optimize acidizing construction parameters and guide acidizing design.

Methodology

Productivity evaluation falls under the category of regression problems in machine learning, which involves using algorithms to learn patterns from geological, engineering, and production data and using those patterns to predict yields. The machine learning method chosen for this study is Gaussian process regression (GPR). It is a non-parametric Bayesian regression approach suitable for small-sample, multidimensional non-linear regression problems [9]. Compared to neural networks and support vector machines, GPR is easier to implement, offers flexible hyperparameter usage, and thus exhibits higher adaptability and generalization capabilities. It finds widespread applications in various fields, including reservoir engineering, electrical engineering, and spectroscopy.

Based on GPR, the acidizing productivity model is given [9]:

$$y_{\mathrm{T}} = f\left(\boldsymbol{x}\right) + \varepsilon_{\mathrm{T}} \tag{1}$$

where x is the input vector and ε_{T} – the corresponds to Gaussian noise. Here, y_{T} follows a Gaussian distribution [9]:

$$y_{\mathrm{T}} \sim GP\left(0, \boldsymbol{K} + \sigma_{\mathrm{n}}^2 \boldsymbol{I}_{\mathrm{n}}\right) \tag{2}$$

where σ_{n}^2 is the variance of the noise, $\boldsymbol{I}_{\mathrm{n}}$ – the n-order identity matrix, and n – the number of samples in the training set. Here, $\boldsymbol{K}$ is the covariance matrix composed of the squared exponential covariance kernel function k [9]:

$$k\left(\boldsymbol{x}_i, \boldsymbol{x}_j\right) = \sigma_h^2 \exp\left[\frac{-\left(\boldsymbol{x}_i - \boldsymbol{x}_j\right)^2}{2\iota^2}\right] \tag{3}$$

where $\boldsymbol{x}_i$ and $\boldsymbol{x}_j$ are the correspond to the i^{th} and j^{th} input vectors in the training set, respectively, σ_{h}^2 – the signal variance of the squared exponential kernel function $k(\boldsymbol{x}_i, \boldsymbol{x}_j)$, and ι – the characteristic length scale of the kernel function $k(\boldsymbol{x}_i, \boldsymbol{x}_j)$. Let $\theta = (\sigma_{\mathrm{n}}^2, \sigma_{\mathrm{h}}^2, \iota)$ be the hyperparameters in the Gaussian process regression model. Based on the negative log-likelihood function $L(\theta)$ of the training samples, these hyperparameters can be determined using the conjugate gradient method [9]:

$$L\left(\theta\right) = -\frac{1}{2}\boldsymbol{Y}_{\mathrm{T}}^{\mathrm{T}}\boldsymbol{Y}_{\mathrm{T}}\boldsymbol{M}^{-1} - \frac{1}{2}\log\left|\boldsymbol{M}\right| + \frac{n}{2}\log 2\pi \tag{4}$$

$$\boldsymbol{M} = \boldsymbol{K} + \sigma_{\mathrm{n}}^2 \boldsymbol{I}_{\mathrm{n}} \tag{5}$$

where M is the intermediate variable and $\boldsymbol{Y}_{\mathrm{T}}$ – the normalized acidizing productivity vector corresponding to the training set. For an individual test sample, its corresponding input vector is $\boldsymbol{x}^*$, which represents the standardized geological and engineering parameters. The output $\boldsymbol{y}^*$ corresponding to $\boldsymbol{x}^*$ also follows a joint Gaussian distribution with $\boldsymbol{Y}$ [9]. There is:

$$\begin{bmatrix} \boldsymbol{Y}_{\mathrm{T}} \\ y_{\mathrm{T}}^* \end{bmatrix} \sim N\left(0, \begin{bmatrix} \boldsymbol{K}(\boldsymbol{X},\boldsymbol{X}) + \sigma_{\mathrm{n}}^2 \boldsymbol{I}_n & \boldsymbol{K}(\boldsymbol{X},\boldsymbol{x}^*) \\ \boldsymbol{K}(\boldsymbol{x}^*,\boldsymbol{X}) & \boldsymbol{K}(\boldsymbol{x}^*,\boldsymbol{x}^*) \end{bmatrix}\right) \tag{6}$$

where $\boldsymbol{Y}$ corresponds to the outputs of the training set. Therefore, the predicted value of the normalized acidizing productivit $\overline{y}_{\mathrm{T}}^*$ can be represented as [9]:

$$\overline{y}_{\mathrm{T}}^* = \boldsymbol{K}(\boldsymbol{x}^*,\boldsymbol{X})\left[\boldsymbol{K}(\boldsymbol{X},\boldsymbol{X}) + \sigma_{\mathrm{n}}^2 \boldsymbol{I}_{\mathrm{n}}\right]^{-1} \boldsymbol{Y}_{\mathrm{T}} \tag{7}$$

where the reverse normalization will yield the corresponding actual value.

Optimizing acidizing construction parameters involves adjusting these parameters to maximize post-treatment productivity. This study utilizes a particle swarm algorithm to optimize acidizing construction parameters. The particle swarm algorithm is a typical intelligent optimization method, which simulates the foraging behavior of birds to find the best solution. The optimization of acidizing construction parameters using the particle swarm algorithm is a process of seeking extremum. The basic operation process is as: Given geological parameters and constraints, based on a well-trained model $F_{\mathrm{M}}(x)$, the particle swarm algorithm is employed to find the maximum value of $F_{\mathrm{M}}(x)$. Specifically, for each well, considering the corresponding geological parameters and in conjunction with on-site construction capabilities, the objective is to maximize post-treatment productivity. The particle swarm algorithm is used to find the acidizing construction parameters that correspond to the maximum value of $F_{\mathrm{M}}(x)$ under these conditions.

Data and model development

Regarding the Deng 4$^{\mathrm{th}}$ Member of the Dengying Formation in the Gaoshiti-Moxi area of the Sichuan Basin, based on the criteria of ease of collection, quantifiability, and comprehensiveness, geological and engineering parameters, as well as production data, were collected from 22 horizontal wells. Geological parameters included: porosity, permeability, water saturation, the proportion of Type I + II reservoirs, the proportion of Type III reservoirs, and the proportion of non-reservoir segments in the acidized wells. Engineering parameters comprised acid strength and injection rate for the acidized wells. The production data were represented as the equivalent test production per kilometer of acidized well. To mitigate the impact of correlations between variables, reduce input parameter redundancy, ease model training, and enhance model interpretability, following prior research, certain parameters were preprocessed as:

– Acid strength = Acid volume/length of the acidized well segment, no longer using acid volume.
– Proportion of Type I + II reservoirs = Thickness of Type I + II reservoirs/length of the acidized well segment, no longer using thickness of Type I + II reservoirs.
– Proportion of Type III reservoirs = Thickness of Type III reservoirs/length of the acidized well segment, no longer using thickness of Type III reservoirs.
– Proportion of non-reservoir segments = Thickness of non-reservoir segments/length of the acidized well segment, no longer using thickness of non-reservoir segments.
– Production per kilometer = Test production of acidized well/length of the acidized well segment × 1000 m, no longer using test production of acidized well.

– The length of the acidized well segment is no longer used the part of the collected geological and engineering data are presented using box plots, as shown in figs. 1 and 2.

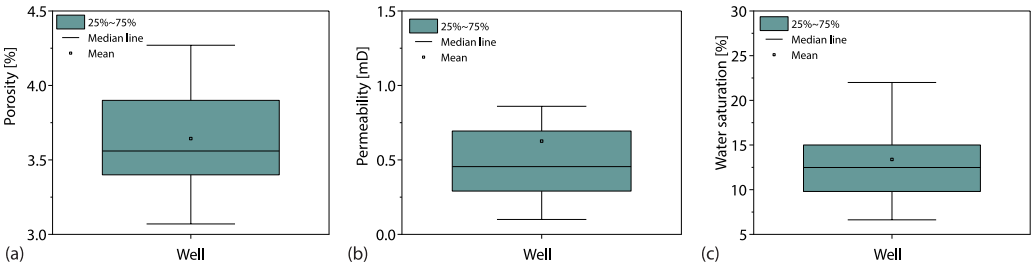

Figure 1. Box plot corresponding to geological data; (a) porosity, (b) bermeability, and (c) water saturation

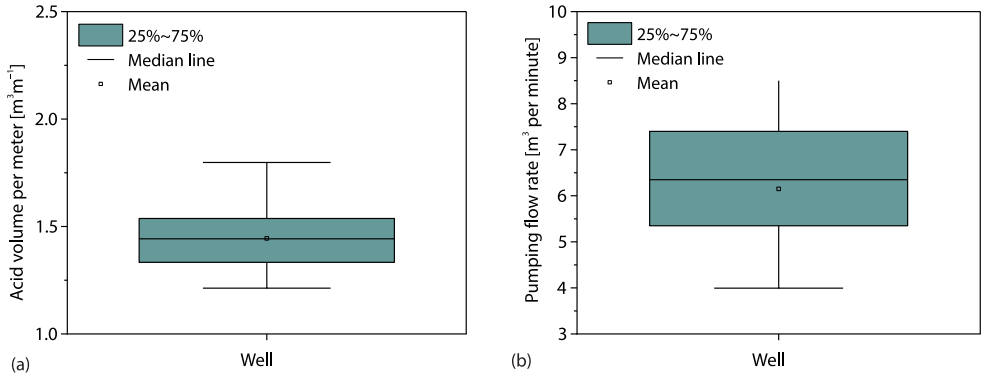

Figure 2. Box plot corresponding to engineering and production data; (a) acid volume per meter and (b) pumping flow rate

Using Gaussian process regression, an acidizing productivity model was established, which represents the relationship between geological and engineering parameters, x_i, and the data of test production per hundred meters, y, *i.e.*, $y = F_M(x_1, x_2, x_3, \ldots, x_n)$. During the modelling process, the collected data were split into a training set and a test set in an 8 : 2 ratio. Thus, 18 acidized wells were used for model training, and four acidized wells were used for model testing. During the model training process, the optimized hyperparameters were $\sigma_n = 1.06 \cdot 10^{-4}$, $\sigma_h = 0.2502$, and $\iota = 1$. The model training and test results are shown in fig. 3. Figure 3 displays that, for both the training and test sets, the model results align closely with the actual test production, with most data points falling within the ±15% error range. For the training set, the model's average relative error is 0.03%, while for the test set, the model's average relative error is 8.77%.

Field application

The MX131 is a horizontal well with a maximum deviation angle of 91.45°, drilled to the Deng 4th member in the Gaoshiti-Moxi area. The total depth of the well is 6310.0 m, with a vertical depth of 5323.82 m. The logging interpretation identified a total of 15 intervals, including 5 gas-bearing intervals and 10 non-gas-bearing intervals. Among the gas-bearing intervals, there were no Type I reservoirs, with a Type II reservoir having an average porosity of 7.09% and a length of 10.25 m. The Type III reservoir had an average porosity of 3.21% and a length of 562.63 m. To enhance reservoir communication, increase reservoir utilization, and ultimately

boost single-well productivity, a self-generated acid pre-flush followed by gelled acid acidizing process was designed, along with segmented open-hole packers for targeted reformation. Utilizing the geological and engineering parameters of the well, the acidizing production model was applied with the objective of maximizing post-treatment productivity, and the particle swarm algorithm was used to optimize the average acid injection rate and acid strength for the acidizing wells, while considering on-site construction capabilities. The upper limits for the injection rate and acid strength were set at 10 m^3 per minute and 2 m^3 per minute, respectively. The optimization process is shown in fig. 4. The results of the optimization indicated an injection rate of 8 m^3 per minute and an acid strength of 1.6 m^3/m, corresponding to a production rate of $68.42 \cdot 10^4$ m^3 per day per kilometer. Based on the optimization results, the designed injection rate was 8 m^3 per minute, and the designed acid strength was 1.6 m^3 per minute. After acidizing, MX131 achieved a test production rate of $60.61 \cdot 10^4$ m^3 per day per kilometer, resulting in a notable production increase. This value was close to the model's predicted value, validating the reliability of the model.

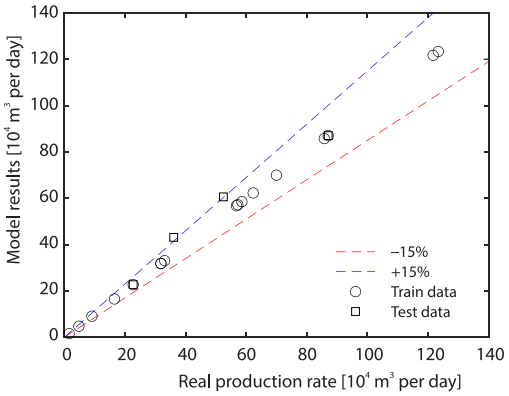

Figure 3. Model results *vs.* real data

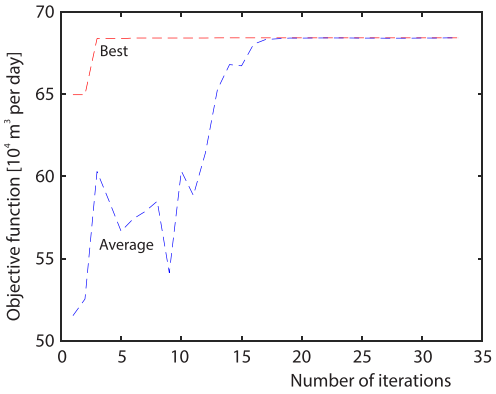

Figure 4. Values of the objective function during iterations

Conclusion

Based on a data-driven approach, a Gaussian process regression model was established for segmented acidized wells to depict the relationship between geological and engineering parameters and test production per kilometer. This model exhibits high accuracy, with an average relative error of only 8.77% for the test dataset. Using the established acidizing productivity model, in combination with the particle swarm algorithm, the acidizing production enhancement plan for well MX131 was optimized. The results demonstrate that the computed optimal acidizing parameters are effective in practice, and the on-site results closely align with the model predictions.

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Nomenclature

M – intermediate variable, [–]

Greeek symbols

ε_T – Gaussian noise, [–]
σ_n^2 – variance of the noise, [–]

References

[1] Xiao, F. J., *et al*., New Understandings of the Seismic Modes of High Productivity Wells in the Sinian Dengying Fm Gas Reservoirs in the Gaoshiti Area, Sichuan Basin, *Natural Gas Industry*, *38* (2018), 2, pp. 8-15
[2] Yue, H., *et al.*, Specified Staged Acid Fracturing of Horizontal Well for Strong-Heterogeneity Carbonate Gas Reservoirs: A Case Study on the Gas Reservoir of the Fourth Member of Upper Sinian Dengying Formation in Gaoshiti-Moxi Area of the Central Sichuan Basin, *Natural Gas Industry*, *41* (2021), 4, pp. 51-60
[3] Gan, X. F., *et al*., Methods to Calculate the Deliverability in Deep Marine Carbonate Gas Reservoirs: Examples from Dengying 4 Gas Reservoirs, Gaoshiti-Moxi Area, Anyue Gasfield, Sichuan Basin, *Natural Gas Exploration and Development*, *45* (2022), 1, pp. 67-73
[4] Lyu, Y. G., *et al*., Study and Application of Acidification Anti Swelling for Low permeability Reservoir with Strong Water Sensitivity, *Chemical Engineering of Oil & Gas*, *47* (2018), 3, pp. 76-79
[5] Sun, C., *et al*., Discussion on Laboratory Evaluation Methods in Acidizing to Dengying Em, Gao-Mo Block, *Chemical Engineering of Oil & Gas*, *46* (2017), 5, pp. 59-64
[6] Hassan, A., *et al*., An Artificial Intelligence-Based Model for Performance Prediction of Acid Fracturing in Naturally Fractured Reservoirs, *ACS omega*, *6* (2021), 21, pp. 13654-13670
[7] Ren, W. X., *et al.*, Analytical Modelling and Probabilistic Evaluation of Gas Production from a Hydraulically Fractured Shale Reservoir Using a Quad-Linear Flow Model, *Journal of Petroleum Science and Engineering*, *184* (2020), 6, 106516
[8] Ren, W. X., *et al*., New Rate-Transient Analysis for Fractured Shale Gas Wells Using a Tri-Linear Flow Model, *Journal of Natural Gas Science and Engineering*, *80* (2020), 8, 103368
[9] Williams, C. K., *Gaussian Processes for Machine Learning*, MIT Press, Cambridge, UK, 2006

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