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Time prediction model of CO_2 channeling for intelligent early warning based on a transfer learning framework

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ABSTRACT

CO_2 flooding technology is a highly efficient method of enhanced oil recovery (EOR), but it can lead to CO_2 channeling, which significantly reduces oil recovery and threatens well safety. Due to the complex geological structure of reservoirs, there is a high level of uncertainty. Traditional numerical simulation and empirical methods are limited in their ability to accurately predict CO_2 channeling, resulting in uncertain channeling times. In addition, there are CO_2 channeling intricately influenced by a multitude of factors, including fluid properties, inter-well connectivity, injection-production mechanisms, and CO_2 channeling capacity, reflecting inherently high-dimensional nature and CO_2 channeling dataset has sparsity. Therefore, it is necessary to introduce a data-driven transfer learning framework to precisely predict the timing of CO_2 channeling. Our proposed framework heavily relies on the Extreme Gradient Boosting (XGBoost) algorithm. Source domains were constructed by learning from various scenarios gas channeling data. The knowledge learned by the source domain model is transferred, allowing for high-precision predictions by simply adjusting parameters for the target domain model. This approach leads to a more comprehensive and accurate analysis of CO_2 channeling times. The model was trained on 120 actual reservoir and 200 simulation well datasets tested on the 18 well datasets of target domain, achieving an average R^2 value of 0.972 and a MSE value is 2393. Distinguished from numerical simulation and empirical formulas, this work presents a novel, swift, and precise to forecasting CO_2 channeling, offering valuable insights for reservoir engineers in managing CO_2 channeling prevention and mitigation strategies.

Keywords: CO_2 channeling, Transfer learning framework, XGBoost algorithm, CO_2 enhanced oil recovery

1. INTRODUCTION

As global warming intensifies, the emission and storage of carbon dioxide have become major concerns worldwide. CO_2-driven CCUS-EOR (Carbon Capture, Utilization and Storage - Enhanced Oil Recovery) technology has emerged as a crucial solution [1~3]. This technology not only facilitates the effective utilization and reduction of CO_2 emissions but also accelerates the achievement of global carbon neutrality. Its widespread application is vital for addressing climate change and achieving sustainable development goals [4].

Carbon dioxide (CO_2) flooding is an effective method for enhancing oil recovery, leveraging the unique physical properties of CO_2, such as viscosity reduction, expansion, and dissolution [5]. These properties enable CO_2 to penetrate oil reservoirs that water flooding cannot reach. When CO_2 mixes with crude oil, it significantly increases the oil mobility, thereby enhancing both microscopic displacement efficiency and oil washing efficiency [6]. However, during the CO_2 flooding process, the substantial differences in viscosity and density between CO_2 and crude oil often lead to gas channeling. This phenomenon can diminish oil recovery rates and negatively impact the overall efficiency of the flooding process. Exploring the timing of CO_2 gas channeling is crucial for enhancing oil recovery. The patterns of gas channeling are influenced by various factors, including injection intensity, injection method, well spacing, and the development of fractures. These factors, combined with the complex and variable geological structures of oil reservoirs, make it difficult to clearly identify gas channeling patterns. Our understanding of subsurface conditions relies primarily on data from logging, core sampling, and other methods. Consequently, when constructing physical information models, we base simulations on existing geological data.

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While this approach is valuable, it also presents limitations.

Predicting the timing of CO_2 gas channeling using solely numerical simulations and empirical formulas may not provide comprehensive and accurate results [7~9]. This necessitates more detailed research and technological innovation. In CO_2 flooding development, gas channeling issues are almost inevitable. Delaying and resolving CO_2 gas channeling problems are crucial for the success of CO_2 flooding development. Therefore, accurately and quickly predicting the timing of CO_2 gas channeling is significant for improving the effectiveness of CO_2 flooding.

The traditional methods for predicting the timing of gas channeling primarily fall into three categories: numerical simulation [10~12], empirical judgment [13~15], and dynamic monitoring [16, 17].

Numerical Simulation Method: This method uses numerical simulation software to model CO_2 flooding development. By setting different injection parameters, it predicts the timing of gas channeling in oil wells and has developed a quantitative method for dividing the stages of CO_2 gas channeling [10]. While this method can control the development process with a certain degree of precision, its accuracy highly depends on the model setup and the accuracy of the actual geological data. Empirical Judgment Method: This method relies on production dynamic parameters during the gas injection development process, such as changes in the gas-oil ratio, recovery rate, composition of well fluid components, as well as gas chromatography and pressure difference methods [11]. By observing the changes in these indicators, it identifies gas channeling. This method is relatively intuitive and depends heavily on field experience. Dynamic Monitoring Method: This includes microseismic monitoring of gas flooding fronts and tracer dynamic monitoring methods. Microseismic technology uses the fluid migration and pressure changes caused by the injected gas, leading to fracture activity, and records this microseismic activity to depict the gas flooding front. The tracer technology monitors fluid seepage channels using tracers, offering high reliability [16]. Currently, many developers prefer to use the empirical judgment method for preliminary gas channeling assessment, followed by more advanced technologies like tracers for fine-tuned control of gas channeling. However, these methods face challenges in identifying the initial stages of gas channeling, relying heavily on field experience, and precisely determining the timing of gas channeling when applied in actual CO2 gas channeling monitoring in fields.

To address the issues of untimely and inaccurate prediction of CO_2 channeling timing, this paper proposes an XGBoost-based model under a transfer learning framework for predicting CO_2 channeling timing. The transfer learning framework typically aims to improve the learning performance of the target learner in the target domain by transferring knowledge from different but strongly related source domains. This approach reduces the reliance on a large amount of target domain data for constructing the target learner, thus achieving an application of transfer learning. In CO2 flooding development, data from field tests have a strong correlation or similarity in dimension with multiple data points in undeveloped reservoirs. This allows the use of a large amount of source domain data to train the XGBoost model. By slightly adjusting the model's hyperparameters, it can be quickly transferred to the target reservoir for prediction. This data transfer mode, under the same characteristic factors, belongs to homogeneous transfer. Often, this transfer strategy can achieve good prediction results even with a small number of training samples or zero samples. Therefore, based on CO_2 channeling data from 120 oil wells in actual reservoirs and data generated from numerical simulation software for 200 oil wells, a source domain model is constructed and then transferred to the target reservoir to predict the channeling timing for each oil well. The prediction performance evaluation achieved an average R2 value of 0.961 and a minimal generalization error of 2.12%. The model performs well, providing accurate CO_2 channeling timing predictions for reservoirs that have not been developed with CO_2 dirve. Based on the predicted different channeling levels of oil wells, corresponding regulatory measures can be formulated, ultimately mitigating channeling while improving CO_2 sweep efficiency and further enhancing recovery rates. The workflow of transfer learning model is shown in Figure 1.

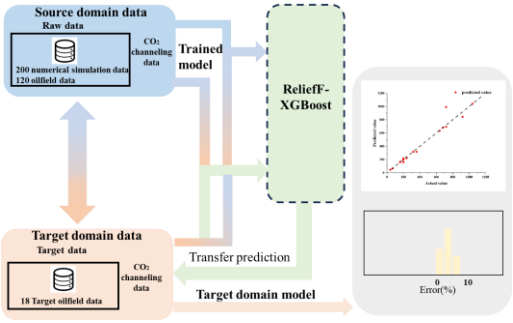

Fig 1. The workflow of transfer learning model

2. METHOD

2.1 Transfer learning framework

The transfer learning framework allows the knowledge from previously learned data (Source domain) to be transferred to future prediction targets (Target domain), continuously sharing data knowledge and enhancing prediction efficiency. This approach can significantly reduce the costs associated with training models and effectively handle complex feature data in the target domain [18~20].

2.1.1 ReliefF feature selection algorithm

ReliefF feature selection algorithm is based on the features of the samples for learning, training [21~23]. one of the samples is randomly selecting from the training data set D of the source domain and target domain. The distance between the other samples to determine the weight of the feature factor. Then it constantly looks for the nearest neighbour samples to update the weight of the feature factor. Finally, the first few items with higher weight of the feature are taken as the main control factor. This feature ranking method is mainly used for dimensionality reduction strategy of 2 different data sets. If the master factors extracted from the two data sets are close, transfer learning can be carried out.

Suppose the set of samples S = {$S1$, $S2$, … … , Sm}, each sample contains p features, si = {$si1$, $si2$, … … , sip}, $1 \le i \le m$. The values of the features are nominal or numerical. The difference between two samples $si$and $sj(l \le i \ne j \le m)$ on feature $t(1 \le t \le p)$ chosen randomly in the training set D is defined as.

If the features of sample R are nominal features for Label Encoding numbering process, you can get the numerical type. If the features of sample R are numerical, using the formula directly for calculation. The specific formula is as follows:

$$diff(t, s_i, s_j) = \begin{cases} 0 & s_{it} = s_{jt} \\ 1 & s_{it} \ne s_{jt} \\ \left|\frac{s_{ir} - s_{jr}}{max_t - min_t}\right| & t\ is\ continuous \end{cases} \quad (1)$$

Where $maxt$ and $mint$ are the maximum and minimum weights of the characteristic factors, respectively; A sample $si$is randomly selected from the sample set D. A sample $si$is taken as the centre .Then k near-neighbour samples nearest to $si$is selected from the samples of the same kind in the sample set. k samples of near Hits are found from the sample set of the same kind. The weight $W(A)$ of this sample is calculated .The weight value $W(A)'$ of this feature is updated.

$$W(A)' = W(A) - \sum_{j=1}^{K} diff(t, s_j, H_j)/(m * k) + \sum_{C \ne class(R)} \left[\frac{p(c)}{1 - p(class(s_i))} \sum_{j=1}^{K} diff(t, s_j, M_j)\right]/(m * k) \quad (2)$$

Where the number of samples sampled is m. The number of nearest neighbour samples k; H_j is the characteristics of similar samples. M_j is the characteristics of dissimilar samples.

ReliefF feaure selction algorithm extracts improtant features in the CO_2 channeling data sample. The high-dimensional features of gas channeling data are mapped to the low-dimensional data space by translation, rotation, inversion and other operations, At the same time, it provides the data feature basis for transfor learning framwork to compare the features of data sets.

2.1.2 Distribution difference metric

Maximum Mean Discrepancy (MMD) is a statistical test method used to measure the difference between two distinct distributions [24]. In machine learning, particularly in transfer learning, MMD helps us understand and measure the difference between the source domain (training data distribution) and the target domain (test data distribution). It is formulated as follows :

$$MMD(X^s, X^T) = \left\| \frac{1}{n^S} \sum_{i=1}^{n^S} \emptyset\left(X_i^S\right) - \frac{1}{n^T} \emptyset\left(x_j^T\right) \right\|_H^2 \quad (3)$$

MMD can be easily computed by using kernel trick. Briefly, MMD quantifies the distribution difference by calculating the distance of the mean values of the instances in an RKHS. The higher Maximum Mean Discrepancy (MMD) value indicates a greater difference between the data structures of the source domain and the target domain, leading to poorer transfer learning performance as the model cannot adequately adapt to the data structure of target domain. Therefore, it is essential to evaluate the source and target domain datasets using MMD before applying transfer learning to devise a reasonable adjustment strategy.

2.1.3 Feaeture Weight adjustment Strategy

In transfer learning, when there are differences in the feature weight rankings between the source domain

and the target domain, it indeed indicates that the reusability of information between these two data sources may vary. In such cases, the model needs appropriate adjustments to better adapt to the characteristics of the target domain's data.

One effective strategy is to reassign the weights of the input features and retrain the model. This typically involves retraining or continuing to train the model, particularly adjusting the weights of those features that are more critical for the target domain. By doing this, the model can focus more on the features that are more important in the target domain, thereby improving its performance in the target domain [25].

Moreover, fine-tuning the target domain model's hyperparameters is also a common approach. Hyperparameter adjustments can include learning rate, batch size, and the number of training iterations, which are crucial factors affecting the model's training and generalization capabilities [26]. Optimizing these hyperparameters can help the model better adapt to the target domain's characteristics. For example, a smaller learning rate might help in making finer adjustments when approaching the optimal solution, while a larger batch size might help stabilize the training process.

2.2 XGBoost model

XGBoost is an ensemble algorithm that leverages the principles of gradient boosting decision trees (GBDT). It relies on an assembly of classification and regression trees (CART) to model data. By sequentially fitting these trees to the training dataset, XGBoost aims to minimize a regularized objective function. This process involves the incremental addition of the outcomes from each tree, which effectively diminishes the model's overall residual and achieves regression [27]. The workflow of XGBoost algorithm is shown in Figure 2.

The primary objective of this regression model is to reduce the difference between predicted and actual values, ensuring the model remains as simple as possible. Consequently, the model utilizes an objective function, which includes both the loss function and a regularization term, as detailed in Equation (4).

$$\begin{cases} obj^{(t)} = \sum_{i=1}^{N} L\left(y_i, \hat{y}_i^{(t)}\right) + \sum_{j=1}^{t} \Omega(f_t) \\ \Omega(f_t) = YT + \frac{1}{2}\lambda \sum_{j=1}^{T} \omega_j^2 \end{cases} \quad (4)$$

$\sum_{i=1}^{N} L\left(y_i, \hat{y}_i^{(t)}\right)$ Is the difference between the predicted value of the model and the true value; T is the number of leaf nodes; ω_j is the fraction of the j-th node; and Y, λ are the hyper-parameters, and penalty coefficients.

In the iterative process, the objective function is reduced to

$$obj^{(t)} = YT + \sum_{j=1}^{T}\left[\sum_{i\in I_j} L\left(y_i, y_i^{(t-1)} + \omega_j\right)\right] + \frac{1}{2}\lambda\omega_j^2 \quad (5)$$

$\sum_{i\in I_i} L(y_i, y_i^{(t-1)} + \omega_j)$ Taylor's second-order expansion at the objective function yields:

$$L\left(y_i, \hat{y}_i^{(t-1)} + \omega_j\right) \approx L\left(y_i, \hat{y}_i^{(t-1)}\right) + L'\left(y_i, \hat{y}_i^{(t-1)}\right)\omega_j + \frac{1}{2}L''\left(y_i, \hat{y}_i^{(t-1)}\right)\omega_j^2 + C \quad (6)$$

The extreme value can be obtained from $\omega_j^* = -\frac{G_j}{H_j+\lambda}$, Let's plug it into equation (6). The optimal value of the objective function is represented in Equation (7), which is instrumental in identifying the best structure for this tree-based ensemble model.

$$minobj = YT - \frac{1}{2}\sum_{j=1}^{T}\frac{G_j^2}{H_j + \lambda} \quad (7)$$

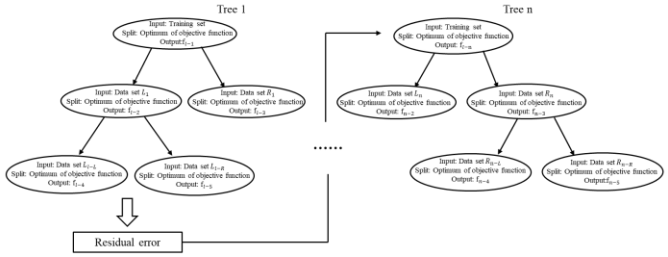

Fig 2. The workflow of XGBoost algorithm

2.3 Evaluation criteria

For the evaluation of the methods, we have chosen the coefficient of determination (R2), mean squared error (MSE), and mean absolute percentage error (MAPE) as the criteria. The mathematical expressions for these metrics are specified below:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (8)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (9)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\% \quad (10)$$

Here, n represents the total number of data points in the dataset, y_i denotes the actual values of CO_2 channeling timing, and $\hat{y}_i$ is the forecasted values. Additionally, $\bar{y}$ refers to the mean of the experimental

values, and $\hat{y}_i$ refers to the mean of the forecasted values.

3. THE APPLICATION OF TRANSFER LEARNING MODEL

3.1 Database

In the process of transfer learning, the quality of data is crucial for the data-driven construction of the source domain model. In this paper, we introduce CO2 channeling data from 120 real reservoirs and 200 numerical simulations. To better construct a source domain model that aligns with physical information, we also collected gas channeling data from 18 wells in the CO2 test area of the Jilin Oilfield for prediction and validation. The data features of model is total 12, as shown in Table 1.

Tab 1. Data feature and their distribution range

Features	Values	Units	Features	Values	Units
Gas injection mode	Continuous gas injection/WAG	/	Divergence factor	Diffusion/ mix/ dissolution in oil and gas	/
Type of channeling channel	Preferential path/ Heterogeneous permeable layer	/	Gas channeling capacity	Good/middle/Bad	/
Cross-flow thickness	0.25~10	m	Reserves	$20\sim80\times10^4$	t
Permeability ratio	0~40	/	Recovery percent of reserves	0~10	%
Gas channeling curve changes shape	Convex rise/ Rise straight/ Rise straight and down	/	Microscopic CO_2 channeling ability	Good/middle/Bad	/
Oil production mode	Continuous/ Periodic/ Unstable oil production/Periodic	/	Cumulative oil production	$2\sim10\times10^4$	t

3.2 Adaptability of the migration model

Based on the optimized results of the data features from both the source and target domain models, we matched these features for comparison. The primary control features, after screening, are presented in Table 2. According to equation (3), the Maximum Mean Discrepancy (MMD) value is 0.12. Before making predictions, the target model, post-transfer, requires parameter adjustments from the original model. The hyperparameters before and after parameter adjustment are shown in the table 3.

Tab 2. The main controlling feature (Source domain model and target domain model)

The main controlling feature of source domain model	Gas injection mode	The main controlling feature of target domain model	Gas injection mode
	Cross-flow thickness		Cross-flow thickness
	Permeability ratio		Permeability ratio
	Reserves		Recovery percent of reserves
	Cumulative oil production		Cumulative oil production

Tab 3. Comparison of XGBoost Model Hyperparameters Before and After Tuning

Parameter Name	Before Tuning	After Tuning
Learning_rate	0.3	0.1
Max_depth	1	5
N_estimators	100	300
Subsample	0.8	0.9

3.3 Performance of CO_2 channeling prediction

In this work, we applied the XGBoost model within a transfer learning framework to analyze 18 wells located in Block X of a specified oil field. The basic characteristics of Block H, relevant to our research, are detailed as follows: Block X is characterized by fault occlusion or lithologic updip pinch-out enrichment, with its oil-bearing properties significantly influenced by physical attributes. It is classified as a lithologic structural oil reservoir. The trial area spans $0.94\ km^2$, with a porosity of 13.0%, an average permeability of $4.5\ mD$, and an initial formation pressure of 24.2 MPa. The geological structure and well location distribution are illustrated in Figure 3.

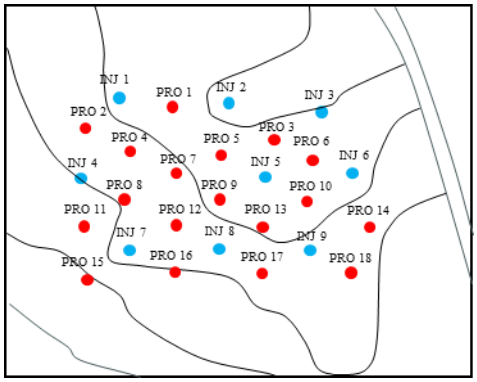

Fig 3. Geological structure map of Block X

Based on the results from Section 3.2, we adjusted some hyperparameters of the source domain model. A comparison between the actual and predicted gas channeling times for the 18 wells is presented in Figure 4. The transfer learning model achieves an average R^2 value of 0.972 and a MSE value is 2393.

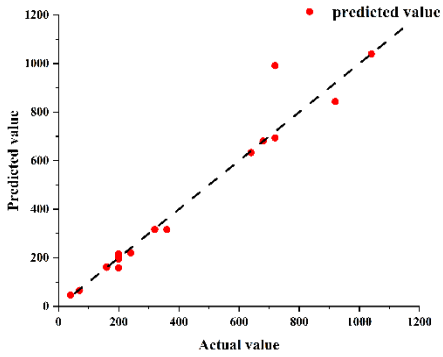

Fig. 4 Comparison of gas channeling prediction results

4. DISCUSSION

The process of transfer learning often raises questions regarding the criteria used to judge the adaptability of the source domain model. Transfer learning involves transferring intrinsic rules (i.e., knowledge) from the training model. The Maximum Mean Discrepancy (MMD) criterion, which is based on the similarity of data points, is commonly used for this purpose. While MMD similarity generally meets the standards of

transfer learning, it can overlook certain physical aspects of the training model.

Despite this limitation, the specific transfer learning process described here aligns well with the characteristics of the data, resulting in no significant differences in MMD. Consequently, the knowledge from the source model is successfully transferred, enabling rapid and accurate predictions.

5. CONCLUSIONS

(1) The transfer learning framework offers an excellent approach to model migration, allowing knowledge acquired from other reservoirs to be transferred to the target reservoir. This not only reduces the cost of model training but also provides accurate and rapid predictions, aiding reservoir engineers in better determining the timing of CO_2 channeling.

(2) The transfer learning model can predict gas channelings in wells in advance, enabling reservoir engineers to make informed decisions based on the timing of CO_2 channeling. This helps to avoid or mitigate the phase of ineffective CO_2 flooding. Moreover, the same transfer learning concept can be applied to various fields such as image recognition, interaction judgment, and safety warnings.

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REFERENCE

[1] Li, H. (2023). Advancing "Carbon Peak" and "Carbon Neutrality" in China: A Comprehensive Review of Current Global Research on Carbon Capture, Utilization, and Storage Technology and Its Implications. ACS OMEGA, 8(45), 42086-42101. https://doi.org/10.1021/acsomega.3c06422

[2] Yang, J., Yang, C., Gu, Q., Zhu, C., Luo, M., & Zhong, P. (2023). Economic evaluation and influencing factors of CCUS-EOR technology: A case study from a high water-bearing oilfield in Xinjiang, China. Energy Reports, 10, 153-160. https://doi.org/https://doi.org/10.1016/j.egyr.2023.06.013

[3] Wang, H., Wen, C., Duan, L., Li, X., Liu, D., & Guo, W. (2024). Sustainable energy transition in cities: A deep statistical prediction model for renewable energy sources management for low-carbon urban development. Sustainable Cities and Society, 107, 105434. https://doi.org/https://doi.org/10.1016/j.scs.2024.105434

[4] Li, K., Shen, S., Fan, J.-L., Xu, M., & Zhang, X. (2022). The role of carbon capture, utilization and storage in realizing China's carbon neutrality: A source-sink matching analysis for existing coal-fired power plants. Resources, Conservation and Recycling, 178, 106070. https://doi.org/https://doi.org/10.1016/j.resconrec.2021.106070

[5] Zhao, Y., Zhang, Y., Lei, X., Zhang, Y., & Song, Y. (2020). CO2 flooding enhanced oil recovery evaluated using magnetic resonance imaging technique. Energy, 203, 117878. https://doi.org/https://doi.org/10.1016/j.energy.2020.117878

[6] Huang, T., Zhou, X., Yang, H., Liao, G., & Zeng, F. (2017). CO2 flooding strategy to enhance heavy oil recovery. Petroleum, 3(1), 68-78. https://doi.org/https://doi.org/10.1016/j.petlm.2016.11.005

[7] Zhao, F. L., Wang, P., Huang, S. J., Hao, H. D., Zhang, M., & Lu, G. Y. (2020). Performance and applicable limits of multi-stage gas channeling control system for CO₂ flooding in ultra-low permeability reservoirs. Journal of Petroleum Science and Engineering, 192, Article 107336. https://doi.org/10.1016/j.petrol.2020.107336

[8] Li, L., Zhou, X. M., Su, Y. L., Xiao, P. F., Chen, Z., & Zheng, J. Y. (2022). Influence of Heterogeneity and Fracture Conductivity on Supercritical CO₂ Miscible Flooding Enhancing Oil Recovery and Gas Channeling in Tight Oil Reservoirs. Energy & Fuels, 36(15), 8199-8209. https://doi.org/10.1021/acs.energyfuels.2c01587

[9] Xu, T., & Wei, Y. (2021). Optimization of Gas Channel Controlling Technique During Co2 Immiscible Flooding in Normal Pressure Tight Oil Reservoir——A Case Study of Honghe Chang 8 Reservoir in South Ordos Basin International Petroleum Technology Conference, https://doi.org/10.2523/IPTC-21334-MS

[10] Chuanzhi Cui (2022). Sweep Characteristics of CO, Miseible Flooding with Injection-Recovery Coupling in Low Permeability Reservoirs and Quantitative Classification of Gas Channeling Stages, Special Oil & Gas Reservoirs, 2022.

[11] Luo, J., & Wang, L. (2022). Research on Gas Channeling Identification Method for Gas Injection Development in High-Pressure Heterogeneous Reservoir. Processes, 10(11), Article 2366. https://doi.org/10.3390/pr10112366

[12] Li, J., Cui, C., Wu, Z., Wang, Z., Wang, Z., & Yang, H. (2022). Study on the migration law of CO2 miscible flooding front and the quantitative identification and characterization of gas channeling. Journal of Petroleum Science and Engineering, 218, 110970. https://doi.org/https://doi.org/10.1016/j.petrol.2022.110970

[13] Gao, Y. C., Zhao, M. F., Wang, J. B., & Zong, C. (2014). Performance and gas channeling during CO₂ immiscible flooding in ultra-low permeability reservoirs. Petroleum Exploration and Development, 41(1), 88-95. https://doi.org/10.1016/S1876-3804(14)60010-0

[14] Sorokin, A. S., Bolotov, A. V., Nuriev, D. R., Derevyanko, V. K., Minkhanov, I. F., & Varfolomeev, M. A. (2022). Dynamic Criteria for Physical Modeling of Oil Displacement by Gas Injection. Processes, 10(12), Article 2620. https://doi.org/10.3390/pr10122620

[15] Balhasan, S., Al Kandari, B., Omar, M., Al-Otaibi, J., Al-Shakhis, H., & Al Amer, A. (2017). Development of an Empirical Equation to Predict the Performance of CO2-WAG Flooding SPE Kuwait Oil & Gas Show and Conference, https://doi.org/10.2118/187539-MS

[16] Warpinski, N. (2009). Microseismic Monitoring: Inside and Out. Journal of Petroleum Technology, 61(11), 80-85. https://doi.org/10.2118/118537-JPT

[17] He, H.-y., Li, C., Zhang, Y., Xin, C.-y., Wang, M., Sun, Y.-c., Shang, L., Jia, Q., & Tian, Z.-j. (2024, 2024//). Research on Gas Drive Front Distribution of Storage in Oil Fields Based on Field Test Monitoring Inversion. Proceedings of the International Field Exploration and Development Conference 2023, Singapore.

[18] Fang, X., Gong, G. C., Li, G. N., Chun, L., Peng, P., & Li, W. Q. (2021). A general multi-source ensemble transfer learning framework integrate of LSTM-DANN and similarity metric for building energy prediction. Energy and buildings, 252, Article 111435. https://doi.org/10.1016/j.enbuild.2021.111435

[19] John, T. A., Dua, I., Balasubramanian, V. N., & Jawahar, C. V. (2022). ETL: Efficient Transfer Learning for Face Tasks Proceedings of the 17th international joint conference on computer vision, imaging and computer graphics theory and applications, vol 5.

[20] Lu, H., Wu, J., Ruan, Y., Qian, F., Meng, H., Gao, Y., & Xu, T. (2023). A multi-source transfer learning model based on LSTM and domain adaptation for building energy prediction. International Journal of Electrical Power & Energy Systems, 149, 109024. https://doi.org/https://doi.org/10.1016/j.ijepes.2023.109024

[21] Fu, Q., Li, Q., Li, X., Wang, H., Xie, J., & Wang, Q. (2024). MOFS-REPLS: A large-scale multi-objective feature selection algorithm based on real-valued encoding and preference leadership strategy. Information sciences, *667*, 120483. https://doi.org/https://doi.org/10.1016/j.ins.2024.120483

[22] Balasubramaniam, S., Vijesh Joe, C., Manthiramoorthy, C., & Satheesh Kumar, K. (2024). ReliefF based feature selection and Gradient Squirrel search Algorithm enabled Deep Maxout Network for detection of heart disease. Biomedical Signal Processing and Control, 87, 105446. https://doi.org/https://doi.org/10.1016/j.bspc.2023.105446

[23] Pan, L.-m., Zhang, M., Ju, P., He, H., & Ishii, M. (2016). Vertical co-current two-phase flow regime identification using fuzzy C-means clustering algorithm and ReliefF attribute weighting technique. International Journal of Heat and Mass Transfer, 95, 393-404. https://doi.org/https://doi.org/10.1016/j.ijheatmasstransfer.2015.11.081

[24] Pan, S. J., & Yang, Q. (2010). A Survey on Transfer Learning. IEEE Transactions on Knowledge and Data Engineering, 22(10), 1345-1359. https://doi.org/10.1109/TKDE.2009.191

[25] Gul, N., Mashwani, W. K., Aamir, M., Aldahmani, S., & Khan, Z. (2023). Optimal model selection for k-nearest neighbours ensemble via sub-bagging and sub-sampling with feature weighting. Alexandria Engineering Journal, 72, 157-168. https://doi.org/https://doi.org/10.1016/j.aej.2023.03.075

[26] Tso, W. W., Burnak, B., & Pistikopoulos, E. N. (2020). HY-POP: Hyperparameter optimization of machine learning models through parametric programming. Computers & chemical engineering, 139, Article 106902. https://doi.org/10.1016/j.compchemeng.2020.106902

[27] Shaik, N. B., Jongkittinarukorn, K., & Bingi, K. (2024). XGBoost based enhanced predictive model for handling missing input parameters: A case study on gas turbine. Case Studies in Chemical and Environmental Engineering, 10, 100775. https://doi.org/https://doi.org/10.1016/j.cscee.2024.100775